Robust planning and control of unmanned aerial vehicles

The Hung Pham

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Robust planning and control of unmanned aerial vehicles

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Abstract

The objective of this thesis is to realize the modeling, trajectory planning, and control of an unmanned helicopter robot for monitoring large areas, especially in precision agriculture applications. Several tasks in precision agriculture are addressed. In pest surveillance missions, drones will be equipped with specialized cameras. A trajectory will be researched and created to enable unmanned aircraft to capture images of entire crop areas and avoid obstacles during flight. Infected areas will be then identified by analyzing taken images. In insecticides spraying, the aircraft must be controlled to fly in a pre-programmed trajectory and spray the insecticide over all the infected crop areas.

In the first part, we present a new complete coverage path planning algorithm by proposing a new cellular decomposition which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a reduced number of cells after decomposition. Genetic Algorithm (GA) and Travelling Salesman Problem (TSP) algorithm are then applied to obtain the shortest path for complete coverage. Next, from the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. Then an algorithm is proposed for generating the best path for a Unmanned Aerial Vehicle (UAV) to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas, and pests-ridden areas.

In the second part, we study the design of a robust control system that allows the vehicle to track the predefined trajectory for a dynamic model-changing helicopter due to the changes of dynamic coefficients such as the mass and moments of inertia. Therefore, the robust observer and control laws are required to adapt the changes in dynamic parameters as well as the impact of external forces. The proposed approach is to explore the modeling techniques, planning, and control by the Linear Parameter Varying (LPV) type technique. To have easily implantable algorithms and adaptable to changes in parameters and conditions of use, we favor the synthesis of Linear Parameter Varying (LPV) Unknown Input Observer (UIO), LPV state feedback, robust state feedback, and static output feedback controllers. The observer and controllers are designed by solving a set of Linear Matrix Inequality (LMI) obtained from the Bounded Real Lemma and LMI regions characterization.

Finally, to highlight the performances of the path planning algorithms and generated control laws, we perform a series of simulations in MATLAB Simulink. Simulation results are quite promising. The coverage path planning algorithm suggests that the generated trajectory shortens the flight distance of the aircraft but still avoids obstacles and covers the entire area of interest. Simulations for the LPV UIO and LPV controllers are conducted with the cases that the mass and moments of inertias change abruptly and slowly. The LPV UIO is able to estimate state variables and the unknown disturbances and the estimated values converge to the true values of the state variables and the unknown disturbances asymptotically. The LPV controllers work well for various reference signals (impulse, random, constant, and sine) and several types of disturbances (impulse, random, constant, and sine).
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<td>PRM</td>
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<td>( \mathbb{N} )</td>
<td>The set of natural numbers</td>
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<td>( \mathbb{Z} )</td>
<td>The set of integers</td>
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<tr>
<td>( \mathbb{R} )</td>
<td>The set of real numbers</td>
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<td>( \mathbb{R}^+ )</td>
<td>The set of non-negative real numbers</td>
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<td>( \mathbb{R}_{&gt;0} )</td>
<td>The set of positive real numbers</td>
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<td>( \mathbb{R}^n )</td>
<td>( n )-dimensional vector space over the field of the real numbers</td>
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<td>( \text{eig}(A) )</td>
<td>The set of eigenvalues of square matrix ( A \in \mathbb{R}^{n \times n} )</td>
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<td>( \sec(x) )</td>
<td>The secant function ( \frac{1}{\cos x} )</td>
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<td>( \succ )</td>
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This chapter briefly introduces the needs of using robots, especially Unmanned Aerial Vehicle (UAV) in Precision Agriculture (PA) for increasing crop yields. Firstly, sustainable food production challenges are given in section 1.1. Then, the definition of PA is introduced in section 1.2. The uses of the mobile robot and UAV in PA are studied respectively in subsections 1.3 and 1.4. Our motivations and the objectives of the thesis are highlighted in section 1.5 and 1.6 respectively. The main contributions are listed in sections 1.7. Finally, the structure of the thesis document is outlined in section 1.8.
Chapter 1. Introduction

1.1 Sustainable food production

According to the Food and Agriculture Organization (FAO, 2009a), it is estimated that by 2050 the world’s population will reach 9 billion and this population change mainly occurs in developing countries [68]. Consequently, ensuring a sustainable supply of food for the world’s fast-growing population is a major challenge. Added to the challenge is that sustainable food products need to be nutrient-dense to allow people to have a diverse diet that contains a balanced and adequate combination of energy and nutrients to support good health [240].

Sustainable food production is "a method of production using processes and systems that are non-polluting, conserve non-renewable energy and natural resources, are economically efficient, are safe for workers, communities and consumers, and do not compromise the needs of future generations" [76].

Although the area of land for agriculture is declining, water resources for cultivation are increasingly scarce, climate change [169], global warming [178], more pests appear, more food still have to be produced. These negative effects on agriculture can be offset to some degree by improving pest control technologies, implementing crop rotations, soil and water conservation, altering crop varieties, employing other sound ecological technologies for resource use in agriculture, and machinery applications in agricultural production.

1.2 Precision Agriculture (PA)

Precision Agriculture (PA) can be defined as "the application of modern information technologies to provide, process and analyze multi source data of high spatial and temporal resolution for decision making and operations in the management of crop production" [47]. The main goal of PA is the process of gathering, processing, and analyzing temporal, spatial, and individual data to support management decision making. This decision greatly affects improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production.

Autonomous robots can be applied in a variety of field operations of PA. The use of Autonomous robots facilitate the processes of capturing and processing high quantities of data. They also provide the required capabilities for operating not only at the individual plant level but also at the complete field level. In [26], authors propose autonomous platforms which can be used for cultivation and seeding, weeding, scouting, application of fertilizers, irrigation, and harvesting.

For the reason that economic benefits should be easily achieved without requiring the integration of additional components or decision support systems, several advanced robotic technologies have been widely applied in PA such as autonomous guidance, autosteer, remote sensing, and controls.

The most important abilities of automatic agricultural robots can be categorized into four categories [40]:

- Guidance: the robot has to self-locate its position in the agricultural environment.
- Detection: the robot should have the ability to detect the biological features from the environment.
1.3. The use of mobile robot in PA

- Action: Based on the information on the first two categories, the robot should execute the task for which the vehicle was designed, such as spraying, monitoring, or harvesting.
- Mapping: the robot could construct the map of the agricultural field.

For accomplishing all the previously mentioned activities, the devices (sensors) such as Real-Time Kinetics Global Positioning System (RTK-GPS), camera, and Light Detection and Ranging (LiDAR) have to retrieve information from the environment and send them to the processing unit of the robot. This information can be the states of the robot (location, velocity, ...) or the information related to the agriculture area. Then, a decision will be made based on the gathered information to accomplish the predefined tasks.

There are several types of agriculture robots. However, they can be defined as two main groups: mobile robot and aerial robot. In the next two subsections, the use of mobile robot and aerial robot in PA will be considered.

1.3 The use of mobile robot in PA

Mobile robots (Fig. 1.1) have been widely used in precision agriculture to reduce human labor and increase productivity. Farmers can use the tractors, harvesters, and they are self-guided by GPS. Robots can automate operations like pruning, thinning, mowing, spraying, and weed removal. Sensor technology is used to manage the pests and diseases that affect crops. Some examples of the application of mobile robot are autonomous targeted spraying for pest control in commercial greenhouses [176], to optimum manipulator design for autonomous de-leafing process of cucumber plants [95], simultaneous localization and mapping techniques for plant trimming [34], automated harvesting of valuable fruits (for example on sweet pepper [184] [94], oil palm [206], mango [209], cucumber [229], almond [227], apple [161] [101], strawberry [91], cherry fruit [215], citrus [147], vineyard [246], and tomato [182] [181] [233]).

Besides mobile robots, flying robots are also widely used in PA. The applications of UAVs will be introduced in the next subsection.
1.4 The use of UAV in PA

The combination of modern technologies such as the Internet of Things (IoT), Information and Communication Technology (ICT), control theory, image processing, and especially the accelerated development of the UAV technology provides a promising solution to deal with the challenges of food sustenation problem. UAVs have been widely used in many applications of PA such as monitoring, weed mapping and management, crop spraying, etc. The specific applications of UAV in PA will be covered in this subsection.

1.4.1 Monitoring

A very common application of PA is to determine the crop health situation by using Remote Sensing (RS) techniques and image analysis. Images can be captured by satellites or UAVs. However, satellite images are not good choice due to the low spatial resolution of acquired images, restrictions of the temporal resolutions as satellites are not always available to capture the necessary images, the quality of the images depends on the weather condition and camera costs. Another method that gives better quality of the images is using the manned aircraft. Though, this method is still costly.

Crops health is a very important factor that determines the quality and quantity of the crop. Therefore, the crops health and diseases detection must be monitored continuously to detect disease promptly and avoid spreading problems. Normally, crop health is often monitored by agricultural experts. Nevertheless, this is a very time-consuming task, as it requires several weeks or even months for inspecting an entire crop and preventing the potentials of “continuous” disease spreading. Another method that can be applied to prevent crop disease is to spray pesticides at fixed times during the plant’s growth. This method has been applied and is relatively popular in developed countries, however, it is high cost and also increases the likelihood of groundwater contamination as pesticide residues in the products and soil.

The applicable of UAV in PA for monitoring the crop’s health conditions provide excellent possibilities to obtain field data in an easy, fast, efficient, and cost-effective way compared to the aforementioned methods. UAVs equipped with specialized cameras are used for gathering photos of the entire plant area. The changes in plant biomass and their health can be determined by using special algorithms for analyzing the crop imaging information. Thus, diseases can be determined in their early stages enabling farmers to intervene in order to reduce losses. For this purpose UAVs can be used in the two different stages of disease control as: (i) UAVs are used to collect crop images. Analyze the gathered images for detecting a possible infection before visual indications appear. Map infected areas for treatment; and (ii) during the treatment of infection, the UAV is used to spray insecticides to precisely the locations of the infected plants that were mapped in the previous period.

1.4.2 Weed mapping and management

Another application of UAV in PA is weed mapping. Weeds are non-desirable crops, they grow simultaneously with the crop in agricultural areas and cause a number of serious problems. They use the same resources such as soil, water, nutrients, and space on agricultural land as crops and affect crop growth. Traditionally, herbicides
are used for controlling the weeds. The same amounts of herbicides are sprayed over the entire field, even within the weed-free areas. Such a strategy incurs a waste of herbicides, potentially contaminating soil resources. Moreover, overuse of herbicides can lead to the evolution of herbicide-resistant weeds and it can affect crop growth and productivity. To overcome the above problems the agriculture area is divided into zones that each one receives customized management because as usual weeds spread through only a few spots of the field. Consequently, it is necessary to generate an accurate weed cover map for precise spraying of herbicide. **UAVs** are used to gathering images. Then, the gathered images are analyzed to generate a precise weed cover map depicting the spots where the chemicals are needed and the needed amount of herbicide for each spot.

### 1.4.3 Crop spraying

The traditional spraying equipment used in conventional farming is the manual air-pressure or battery-powered knapsack sprayers. However, this traditional spraying equipment causes a non-minor loss of pesticides due to the mechanical structure of the injector and the spraying is done manually. Furthermore, the operators have to be present when spraying, resulting in contact with operators and possibly affecting human health.

Therefore, the use of **UAVs** to spray pesticides [217][235][69][81][244] can reduce the operator’s exposure to chemicals, reduce pesticide losses, and save time. An uncrewed helicopter, which is equipped with small pesticide tanks, was developed and introduced in Japan in the 1980s [212] for crop spraying. By analyzing image data, we can determine exactly and pest status of the crop on the whole area of agriculture. Because the level of plant pests and diseases varies from region to region, the amount of insecticide to be sprayed must also be different to ensure uniform plant growth. Path planning algorithms based on crop data not only create the optimal motion trajectory for the **UAV** but also optimize the amount of needed agrochemical products.

### 1.4.4 Irrigation management

Currently, the process of irrigation for crops consumes about 70% of the water in the world. [38][196], while water resources are increasingly exhausted. Therefore, crop irrigation management [190][12][168][183] is a very important task in **PA**. Precision irrigation techniques must be improved and monitored more strictly to lead to the more efficient use of water: (i) in the right place; (ii) at the right time; and (iii) in correct quantities.

Typically, water is evenly irrigated over the entire crop area, although the amount of water actually needed for different areas varies. Therefore, determining the appropriate amount of water to irrigate in different areas can help farmers save time and water resources. Moreover, such precise farming techniques can lead to increased yields and crop quality. Dividing agricultural land into different irrigation areas, for precise management of resources, can be done easily by using **UAV**. Special sensors equipped on the **UAVs** give them the ability to classify and identify areas where plants need more water. Besides, based on data collected from **UAV** we can create specialized maps that illustrate the morphology of the soil for more efficient irrigation, suitable for each type of crop and each specific area.
Table 1.1: The use of autonomous robot in PA

<table>
<thead>
<tr>
<th>Publication</th>
<th>Robot type</th>
<th>Operation</th>
<th>Technique</th>
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<tbody>
<tr>
<td>180</td>
<td>Aerial robot</td>
<td>Monitoring Process - Monitoring vegetation state</td>
<td>Multispectral camera, GPS system, FlightCTRL, NaviCtrCTRL, First person view platform, GSM modem, Magnetic compass</td>
</tr>
<tr>
<td>13</td>
<td>Aerial robot</td>
<td>Monitoring Process -Detecting drainage pipes</td>
<td>VIS Camera, NIR Camera, Thermal Camera</td>
</tr>
<tr>
<td>110</td>
<td>Aerial robot</td>
<td>Monitoring Process -Evaluating water stress and vegetation state</td>
<td>Thermal camera, Multispectral camera, Single-board computer, GPS system, Stabilization mechanism</td>
</tr>
<tr>
<td>249</td>
<td>Aerial robot</td>
<td>Monitoring Process - Estimating nitrogen state</td>
<td>Hyperspectral camera</td>
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<tr>
<td>49</td>
<td>Aerial robot</td>
<td>Spraying Process - Spraying fruits and trees</td>
<td>Spraying Device, Multispectral camera, IMU, Magnetometer. Barometer, Servos</td>
</tr>
<tr>
<td>193</td>
<td>Aerial robot</td>
<td>Investigating computational resources during a monitoring process</td>
<td>IMU, GPS system</td>
</tr>
<tr>
<td>198</td>
<td>Aerial robot</td>
<td>Evaluating water stress</td>
<td>FlightCtrl, NaviCtrl, 3-axis accelerometer, Thermal Camera, Storing device, Pressure sensor, Digital compass, GPS system</td>
</tr>
<tr>
<td>228</td>
<td>Mobile robot</td>
<td>Coverage path planning</td>
<td>Harmony Search (HS) algorithm for finding complex coverage trajectories</td>
</tr>
<tr>
<td>192</td>
<td>Mobile robot</td>
<td>Field mapping</td>
<td>3D terrain maps, stereo camera, location sensor, IMU</td>
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<td>199</td>
<td>Mobile robot</td>
<td>Weed and pest control</td>
<td>Image processing, decision control algorithms</td>
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<tr>
<td>217</td>
<td>Mobile robot</td>
<td>Weeding</td>
<td>Automatic computer vision, differential spraying to control the weeds.</td>
</tr>
</tbody>
</table>

### 1.4.5 Vegetation growth monitoring and yield estimation

UAVs are also often applied in monitoring vegetation growth and providing estimates of productivity \[250, 230, 106, 92\]. One of the main major difficulties of increasing agricultural
productivity and quality is the lack of means to systematically monitor the process of cultivation. Therefore, collecting and analyzing information related to crop growth regularly using the UAV provide an increased opportunity to track crop growth and observe changes in some parameters of the field.

Many works have been focusing on observing the biomass and nitrogen status of crops besides the yield estimation. Biomass of crops and nitrogen content status are the main parameters to determine the need for additional fertilizer or other actions. Furthermore, various parameters, such as crop height, the distance between rows or between plants, and the index Leaf Area Index (LAI) can be estimated by using the three-dimensional digital maps of the crop which is created by the gathered images by the UAVs. By analyzing the information gathered about crops by UAV, farmers can make plans to control crop management, decide when to irrigate, spray pesticides, or harvest.

Table 1.1 provides examples of the developments of autonomous mobile and aerial robots in PA.

1.5 Motivations

We are motivated, in this thesis, by the coverage path planning scenario and control of Unmanned Aerial Vehicle (UAV) in Precision Agriculture (PA) for the two tasks, crop inspection and crop spraying.

Although the application of Unmanned Aerial Vehicle (UAV) in Precision Agriculture (PA) has been being studied intensively, however, many challenges are still open with respect to the coverage path planning scenarios as the requirements to visit all the predefined points while avoiding obstacles and minimize some objective functions.

In the control aspect, the UAV has to follow as most accurately as possible according to the given trajectory under the influence of disturbances such as wind or changes of dynamic parameters such as mass or moments of inertia during flying time.

1.6 Objectives

The objective of this thesis is to realize the modeling, planning, and control of an unmanned helicopter robot for monitoring large areas, especially in PA applications. Several tasks in PA are addressed such as monitoring, insecticides spraying.

- **Path planning objective**: In pest surveillance missions, drones will be equipped with specialized cameras. In order to monitor the whole agriculture area, we need to capture images by specialized cameras. A trajectory will be researched and generated to enable the UAV to capture images of entire crop areas and avoid obstacles during flight. Infected areas will be then identified by analyzing gathered images.

- **Control objective**: In insecticides spraying, the UAV must be controlled to fly in a pre-programmed trajectory, which has been generated in the path planning task, and spray the insecticide over all the infected crop areas. The UAV is equipped with pesticide tank and a mechanical or hydraulic system for pesticide spraying. During the spraying of insecticides, the mass of UAV will decrease over time, resulting in changes
in the dynamic parameters of \textbf{UAV} such as the moments of inertia. In addition, during the mission, \textbf{UAV} is affected by disturbances such as wind gusts. The changes in the kinetic parameters and the external disturbances cause instability of the \textbf{UAV}. Consequently, a robust controller has to be designed to stabilize the \textbf{UAV} and to follow exactly the predefined trajectory while keep stabilizing the \textbf{UAV} under the changes in the kinetic parameters and the external disturbances.

1.7 Contribution of the thesis

The objective of this thesis is to realize the modeling, planning, and control of an unmanned \textbf{UAV} robot for monitoring large areas, especially in \textsuperscript{1}Precision Agriculture\textsuperscript{1} (PA) applications. Several tasks in \textsuperscript{1}PA\textsuperscript{1} are addressed. In pest surveillance missions, drones will be equipped with specialized cameras. A trajectory will be researched and created to enable unmanned aircraft to capture images of entire crop areas and avoid obstacles during flight. Infected areas will be then identified by analyzing taken images. In insecticides spraying, the aircraft must be controlled to fly in a pre-programmed trajectory and spray the insecticide over all the infected crop areas.

In the first part, we present a new complete coverage path planning algorithm by proposing a new cellular decomposition which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a decrease in the number of cells after decomposition. \textsuperscript{2}Genetic Algorithm\textsuperscript{2} (GA) and \textsuperscript{3}Travelling Salesman Problem\textsuperscript{3} (TSP) algorithm are then applied to obtain the shortest path for complete coverage. Next, from the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. Then an algorithm is proposed for generating the best path for a \textbf{UAV} to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas, and pests-ridden areas.

In the second part, we study the design of a robust control system that allows the vehicle to track the predefined trajectory for a dynamic model-changing \textbf{UAV} due to the changes of dynamic coefficients such as the mass and moments of inertia. Therefore, the robust observer and control laws are required to adopt the changes in dynamic parameters as well as the impact of external forces. The proposed approach is to explore the modeling techniques, planning, and control by the \textsuperscript{4}Linear Parameter Varying\textsuperscript{4} (LPV) type technique. To have easily implantable algorithms and adaptable to changes in parameters and conditions of use, we favor the synthesis of \textsuperscript{5}Unknown Input Observer\textsuperscript{5} (UIO), \textsuperscript{4}LPV\textsuperscript{4} quadratic state feedback, dynamic output feedback, and static output feedback controllers. The observers and controllers are designed by solving a set of Linear Matrix Inequality (LMI) obtained from the Bounded Real Lemma and LMI region characterization.

Finally, to highlight the performance of the path planning algorithms and generated control laws, we perform a series of simulations in MATLAB Simulink environment. Simulation results are quite promising. The coverage path planning algorithm suggests that the generated trajectory shortens the flight distance of the aircraft but still avoids obstacles and covers the

\textsuperscript{1}Precision Agriculture (PA)
\textsuperscript{2}Genetic Algorithm (GA)
\textsuperscript{3}Travelling Salesman Problem (TSP)
\textsuperscript{4}Linear Parameter Varying (LPV)
\textsuperscript{5}Unknown Input Observer (UIO)
entire area of interest. Simulations for the $\text{LPV UIO}$ and $\text{LPV}$ controllers are conducted with the cases that the mass and moments of inertia change abruptly and slowly. The $\text{LPV UIO}$ is able to estimate state variables and the unknown disturbances and the estimated values converge to the true values of the state variables and the unknown disturbances in a short time. The $\text{LPV}$ controllers work well for various reference signals (impulse, random, constant, and sine) and several types of disturbances (impulse, random, constant, and sine).

1.8 Structure of the thesis

The manuscript of the thesis is divided into 7 chapters:

- **Chapter 1 - Introduction**: Introduces the applications and necessity of robots, especially $\text{UAV}$s in $\text{PA}$. Moreover, it highlights our motivations, the specific challenges, objectives, and the main contributions of the thesis.

- **Chapter 2 - State of the art**: offers a short state of the art for $\text{UAV}$s and more particularly the multirotors as typical vehicle for coverage path planning mission. Then, it also reviews the state of the art of the coverage path planning algorithms and control laws for quadcopters.

- **Chapter 3 - System modeling**: introduces the mathematical differential equations of quadcopter dynamics.

- **Chapter 4 - Robust path planning**: proposes a new approach for maximizing the coverage path planning while minimizing the path length of an aerial robot in agriculture environment with concave obstacles. For resolving this problem, we propose a new cellular decomposition which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a decrease of the number of cells after decomposition. The results show that this new cellular decomposition works well even with several concave obstacles inside the environment. Furthermore, for path planning, the cells are divided again into two classes, leading to have a cell set better suited for use of the $\text{TSP}$ to get complete coverage. $\text{GA}$ and $\text{TSP}$ algorithm are applied to obtain the shortest path. Then, an approach is also proposed to maximize the scanned area on the working area with obstacles. Then, we focus on generating the best path for an $\text{UAV}$ to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas and pests-ridden areas. The algorithm for generating this trajectory can save the working time and the amount of medicine to be distributed to the whole agriculture infected areas.

From the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. There is a trade-off between the number of classes generated and the area of all the pests-ridden areas. After that, a polygon will be found to cover each of these infected regions. However, obstacles may occupy part of the area of these polygons that have been created previously. Each polygon that is occupied in part by obstacles can be further divided into a minimum number of obstacle-free convex polygons. Then, an optimal path length of boustrophedon trajectory will be created for each convex polygon that has been
created for the UAV to follow. Finally, this chapter deals with the process of creating a minimal path for the UAV to move between all the constructed convex polygons and generation of the final trajectory for the UAV which ensures that all the infected agriculture areas will be covered by the medicine.

- **Chapter 5 - Control**: During the spraying of insecticides, the mass of UAV will decrease over time, resulting in changes in the dynamic parameters of UAV such as the moments of inertia. In addition, during the mission, UAV is affected by disturbances such as wind. The changes in the kinetic parameters and the external disturbances cause instability of the UAV. Therefore, several robust control laws for quadcopter under disturbances and changes of the dynamic parameters have been developed such as LPV dynamic output feedback controller, LPV static output feedback controller, and LPV state feedback controller. We also design a Linear Parameter Varying (LPV) Unknown Input Observer (UIO) for quadcopters.

- **Chapter 6 - Simulation and experiments**: The simulations are conducted for both path planning and control tasks. This chapter also gives some comments on the simulation results and will discuss the advantages and performances of the proposed approaches.

- **Chapter 7 - Conclusion and perspectives**: Gives some concluding remarks as well as perspectives.

1.9 Publications

This work results in several publications in international conferences proceedings. Journal papers are submitted and are under review.

Published:


To be submitted:

• T. H. Pham, D. Ichalal, S. Mammar. "Discrete LPV state feedback preview control design for Attitude/Altitude of a mass-varying quadcopter".

• T. H. Pham, D. Ichalal, S. Mammar. "Attitude/Altitude LPV UIO-based controller design of a mass-varying quadcopter".

• T. H. Pham, D. Ichalal, S. Mammar. "Complete coverage path planning using UAV applied in precision agriculture under the consideration of dynamic constraints."
This chapter offers a brief state of the art of Unmanned Aerial Vehicle (UAV). Firstly, a short review of UAV such as UAV classification, applications, advantages, and disadvantages of UAV will be given in Section 2.1.1. Due to their special characteristics, which allow their use in a wide range of applications, we focus on particular Vertical Take-Off and Landing (VTOL) types of UAVs and especially the quadrotor configuration in Section 2.2. Then the state of the arts of complete coverage of UAV and control of quadrotors are given in Section 2.3 and 2.4 respectively.

This Chapter contains:

2.1 Unmanned Aerial Vehicles
   2.1.1 Overview of unmanned aerial vehicles
   2.1.2 UAVs classification
   2.1.3 Applications of UAVs
   2.1.4 Advantage, disadvantages, and typical uses of UAVs
      2.1.4.1 Fixed Wing UAV
      2.1.4.2 Single Rotor UAV
      2.1.4.3 Multirotors UAVs

2.2 Quadrotors

2.3 Coverage Path planning methods used for UAV
   2.3.1 No Decomposition
   2.3.2 Cellular Decomposition (CD)

2.4 State of the art on the control of quadcopters
   2.4.1 Proportional Integral Derivative controller
   2.4.2 Linear Quadratic Regulator (LQR)/Gaussian LQR/G
   2.4.3 Sliding Mode Control (SMC)
   2.4.4 Backstepping Control
   2.4.5 Adaptive Control Algorithms
   2.4.6 Robust Control Algorithms
   2.4.7 Optimal Control Algorithms
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2.5 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 35
2.1 Unmanned Aerial Vehicles

2.1.1 Overview of unmanned aerial vehicles

An Unmanned Aerial Vehicle (UAV) or drone is an aircraft without passenger or pilot on-board which can fly autonomously based on pre-programmed flight plans, through the help of complex dynamic automation systems, or be controlled remotely by a pilot at a ground control station. Depending on its mission, endurance, and size, each UAV can carry different payloads.

UAVs are equipped with multiple sensors (such as Global Positioning System (GPS), Inertial Measurement Unit (IMU), Differential Global Positioning System (DGPS), accelerometer, magnetometer, pito tube, etc) and are connected in real time to many other systems at the ground control station. This allows the UAV to gain important information such as speed, position, heading, altitude, movement direction, temperature, speed and wind direction, the amount of fuel or remaining energy to perform the task, etc. UAV can perform a variety of tasks in military, civilian, and entertainment applications. Moreover, since they are free of screw on board, they can be designed to be smaller, can perform tasks that require greater flexibility, and can carry more payloads.

2.1.2 UAV classification

There are many characteristics for classifying UAVs based on their variety intended use.

Classification according to size

- Very small UAVs: are the unmanned aircraft with dimensions ranging from the size of a large insect to 30 [cm] – 50 [cm] long. The very small UAVs can be sub-divided into
  - Micro or nano UAVs: insect size is up to 15 [cm].
  - Mini UAVs: insect size is between 15 [cm] and 50 [cm].

The representative of very small UAVs is insect-like UAVs. Their popular micro design always has flapping or rotary wings. They are extremely small in size, very lightweight, and can be used for spying and biological warfare. Some of nano UAVs are shown in Fig. 2.12 Examples of mini UAVs are Xbird 250 quadro, Parrot bebop, Parrot Disco, (a) Black Hornet (b) Hummingbird (c) Hummingbird (d) Dragonfly robot

Figure 2.1: Nano UAV robots and Eagle VTOL Mapping in Fig. 2.10.
Chapter 2. State of the art

- **Small UAVs**: are the class that have at least one dimension greater than 50 cm and no larger than 2 meters. Most of them are hand-launched by throwing in the air while some other are of fixed-wing model. Examples of small UAVs are RQ 11 Raven with a wingspan of 1.4 m, RQ 7 Shadow, RS 16 is a crossover between a small and a medium sized system, and Turkish Bayraktar which weight is 5 kg and has a range of 20 km in Fig. 2.3.

- **Medium UAVs**: are the class that are too heavy to be carried by one person but are still smaller than a light aircraft. They usually have a wingspan of about 5-10 m and can carry payloads of 100 to 200 kg. Some medium fixed-wing UAVs are shown in Fig. 2.4. There are also numbers of medium sized UAVs in the form of rotary-based.

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**Figure 2.2**: Mini UAV robots

(a) Xbird 250 quadro  
(b) Parrot bebop  
(c) Parrot Disco  
(d) Eagle VTOL Mapping

**Figure 2.3**: Small UAV robots

(a) RQ 11 Raven  
(b) RQ 7 Shadow  
(c) RS 16  
(d) Turkish Bayraktar

**Figure 2.4**: Medium UAV robots

(a) UK Watchkeeper  
(b) RQ 2 Pioneer  
(c) RS 20  
(d) Eagle Eye
2.1. Unmanned Aerial Vehicles

- Large UAVs: applies to the large UAVs and used mainly by the military. Some of large UAVs such as Atomics MQ-1 Predator, Global Hawk, Harfang, and MQ 1C Warrior are shown in Fig. 2.5.

![Atomics MQ-1 Predator](image1)
![Global Hawk](image2)
![Harfang](image3)
![MQ 1C Warrior](image4)

**Figure 2.5:** Large UAV robots

Classification of UAVs according to its range of action

- High-altitude long-endurance (HALE): this types of UAVs can flight over 15000[m] altitude and more than 24[hr] of endurance. These UAVs are usually used for surveillance mission. Two example of HALE UAVs are Northrop Grumman's Global Hawk and Agilis HALE UAV in Fig. 2.6.

![Northrop Grumman's Global Hawk](image5)
![Agilis HALE UAV](image6)

**Figure 2.6:** High-altitude long-endurance (HALE) UAV robots

- Medium-altitude long-endurance (MALE): the altitude for this types of UAVs is about 5000[m] to 15000[m] with 24[hr] maximum of endurance. These UAVs are also used for surveillance mission but with shorter ranges. Two example of MALE UAVs are Persistent UAS Platforms and Agilis HALE UAV in Fig. 2.7.

- Medium-Range or tactile UAV (TUAV): the range of flight for this type of UAVs is between 100[km] and 300[km]. The TUAVs IAI Heron (Machatz-1) and AAI (Textron) RQ-7 Shadow are shown in Fig. 2.8.

- Close-range UAV: The close range UAVs can operate within the range less than 100[km]. This type of UAVs is mainly used for traffic monitoring, powerline inspection, surveillance, or crop-spraying in precision agriculture. The close range UAV Optimus UAV and RemoEye 006 are shown in Fig. 2.9.
Chapter 2. State of the art

(a) Persistent UAS Platforms

(b) WK-450 Watchkeeper

Figure 2.7: Medium-attitude long-endurance (HALE) **UAV** robots

(a) IAI Heron (Machatz-1)

(b) AAI (Textron) RQ-7 Shadow

Figure 2.8: Medium-Range or tactile **UAV** (TUAV) robots

(a) Optimus UAV

(b) RemoEye 006

Figure 2.9: Close-Range **UAV**

- **Mini UAV** (MUAV): The operation range for mini **UAVs** is up to 30[km] and their weight is less than 20[kg]. The mini **UAVs** Orbiter Mini UAV and Skylark 1 LE Mini are shown in Fig. 2.10

(a) Orbiter Mini UAV

(b) Skylark 1 LE Mini

Figure 2.10: Mini **UAV** robots
2.1. Unmanned Aerial Vehicles

- Micro UAV (MAV): the wingspan is less than 150 [mm]. This type of UAVs are mainly used in urban environments or for indoor applications. Due to the small size, the micro UAVs are very vulnerable to the wind.

![Micro UAV NX70](image1)

![Honeywell RQ-16 T-Hawk](image2)

**Figure 2.11: Mini UAV robots**

- Nano Air Vehicle (NAV): the size is of 10 [mm]. The Nano UAVs, The Hornet 2-b (Prox Dynamics) and Nano UAV Hornet 3 Prox Dynamics in Fig. 2.12a are complete with camera and video transmitter.

![The Hornet 2-b (Prox Dynamics)](image3)

![Nano UAV Hornet 3 Prox Dynamics](image4)

**Figure 2.12: Nano UAV robots**

- Remotely piloted helicopter (RPH): are UAVs that are capable of vertical take-off and landing automatically with pre-programmed programs. This type of aircraft is often used in missions that require hovering flight such as inspection or surveillance. Remotely piloted helicopters Long Endurance Fuel Power Fixed Wing gasoline VTOL UAV and Terrafugia TF-2 Tiltrotor are shown in Fig. 2.13

![Long Endurance Fuel Power Fixed Wing gasoline VTOL UAV](image5)

![Terrafugia TF-2 Tiltrotor](image6)

**Figure 2.13: Nano UAV robots**
2.1.3 Applications of UAVs

Nowadays, the uses of UAVs with diverse capabilities for both civilian and military applications are growing very fast. Moreover, there is a significant interest in the development of novel drones that can operate autonomously in different types of complicated environments and locations. UAVs can perform various missions in complicated environments both outdoor and indoor. Drones can be equipped with various sensors and cameras. Consequently, UAVs are capable of performing accurate and reliable tasks of intelligence, surveillance, and reconnaissance missions. The missions of UAVs can be categorized as for the military or civil, type of the flight zones (outdoor or indoor), and type of the environments (air/space) as shown in Figure 2.14.

**Figure 2.14: Classification of drones’ applications**

**Search and rescue missions**

A really important application of UAVs is to search and rescue missions. A search and rescue UAV is usually used by emergency services, such as police officers, firefighters, or rescue teams. Every second is vital in search and rescue operations. In order to most effectively deploy rescue missions, we need to understand and get a quick overview of the situation. While manned aerial vehicles and helicopters require time to be ready for operating the mission, drones can be operated instantaneously without any preparation time. Unmanned aerial vehicles UAVs can provide real-time visual information and data in the aftermath of an earthquake or hurricane. They can also become an eye in the sky to locate a lost person in the mountain for example. Thanks to high mobility, quick deployment, able to operate in complex environments including small environments such as caves, this type of UAVs is ideal for searching over vast areas for missing persons in need of rescue and in any environment.
Environmental protection

Besides rescue or military applications, UAV is also increasingly applied in environmental management such as managing agricultural lands, real-time weather condition and forecast, observing the effects of climate change, monitoring the biodiversity of different ecosystems from rain forests to the oceans, monitoring crops pest, and tracking wildlife in different areas [219].

Mailing and delivery

Unmanned delivery service is attracting the attention of big companies in the world such as Amazon, Google [224] [87]. More and more companies are using drones to deliver products to their customers. To accomplish this, the UAV is equipped with the ability to vertically take off and land.

Drone in Precision Agriculture (PA)

With increasing populations, the demand for food is increasing. The latest advanced technologies should be applied in agriculture to meet this growing demand. Several types of robots have been designed for using in PA such as mobile robots for harvesting, crops monitoring. With the introduction of low-cost drones with advanced capabilities, the use of UAVs in precision agriculture is growing really fast. Drones are playing a significant role in optimizing agriculture operations. Thanks to the help of drones, agricultural activities such as crop management, crop counting, crop health monitoring, and spraying pesticides can be operated more cost-effectively and more quickly as compared to conventional methods, which typically rely on the use of piloted aircraft.

2.1.4 Advantage, disadvantages, and typical uses of UAVs

In the previous subsection, we have examined the classification and applications of UAVs. In this chapter, we examine the advantages and disadvantages of UAVs for the fixed-wing UAV, single rotor UAV and multirotor UAV

2.1.4.1 Fixed Wing UAV

Fixed-wing UAVs use a wing like a normal aeroplane to provide the lift by the aircraft’s forward motion. Fixed-wing UAVs can be self-propelled, pure gliders (vehicles whose free flight does not rely on a method of propulsion) or a mixture of the two. Fixed-wing UAVs can be distinguished to the other types of UAVs that they cannot stay hovering in one place with vertical lift rotors in the air.

Fixed wing UAVs are well known in the military, as they are often used when manned flight is considered too risky or difficult. They are also used in the commercial industry, monitoring, etc.

Advantages:

- The operating time of fixed-wing UAVs can be a couple of hours and can up to 16 hours or more.
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- Fixed-wing UAVs can fly at a high altitude.
- Fixed-wing UAVs have the ability to carry more weight.

Disadvantages:
- Fixed-wing UAVs are usually expensive.
- Training is usually required for flying.
- Launcher or long runway are needed to get a fixed-wing UAVs into the air.
- It is required the runway, parachute, or special method for landing (recovering) the UAVs.
- Fixed-wing UAVs can’t hover in the air.

Typical uses:
- The fixed-wing UAVs are usually used for commercial purposes such as aerial mapping, inspection, agriculture, construction, security, and surveillance due to the ability of long endurance, high altitude, and long operating fly time.

2.1.4.2 Single Rotor UAV

While a multi-rotor UAV has many different rotors to hold it up, a single rotor UAV has just one rotor, plus a tail rotor to control its heading.

Advantages:
- A single rotor UAVs have the benefit of much greater efficiency over a multi-rotor,
- Long flying time if they are powered by a gas motor.
- Single rotor UAVs are able to hover vertically in the air.
- Single Rotor UAVs are strong and durable.
- Heavy payload capability.

Disadvantages:
- Single Rotor UAVs are harder to fly than multi-rotor UAV types.
- Single rotor UAVs can be expensive.
- Single rotor UAVs have a higher complexity.
- Single rotor UAVs can be dangerous because of their heavy spinning blade.

Typical uses:
- Surveying, research, Aerial LIDAR laser scan.

2.1.4.3 Multirotors UAVs

A multirotor UAV is one of the robots that has the ability to achieve agile motion in the air. Unlike fixed-wing UAVs multirotor UAVs rely on the rotation of rotors to generate power, which will generate powerful airflow. This is the popular choice for aerial photography, film
2.2. Quadrotors

Multirotor UAVs carry several rotors on their body and can be further classified based on the number of them on the platform of the drone. There are tricopters (3 rotors as in Figure 2.15a, 2.15b), quadcopters (4 rotors as in Figure 2.15c, 2.15d), hexacopters (6 rotors as in Figures 2.15e, 2.15f, 2.15g, 2.15h, 2.15i) and octocopters (8 rotors as in Figures 2.15j, 2.15k, 2.15l, 2.15m, 2.15n, 2.15o). The most commonly used of Multirotor UAVs are quadcopters.

Advantages:

• Simpler rotor mechanics required for flight control, easy for maintenance.
• Multirotor UAVs are easy control and maneuver.
• Multirotor UAVs have the ability to hover in the air.
• Multirotor UAVs can take off and land vertically.
• Multirotor UAVs are very stable.

Disadvantages:

• Low flying time (usually 15-30 minutes).
• Multirotor UAVs are limited on payload capability.
• Multirotor UAVs’s energy is spent on fighting gravity and stabilizing in the air.

Typical uses:

• Aerial photography and video aerial inspection, leisure, agriculture, construction, security.

2.2 Quadrotors

Based on the analysis of the advantages and disadvantages of different types of UAVs as detailed in the previous subsection, we choose quadrotor as the research object in the content of this thesis. The main features of the quadrotor will be considered in more detail in this subsection.

A quadcopter is a helicopter that consists of a rigid cross-frame equipped with four rotors $M_1$, $M_2$, $M_3$, and $M_4$ as shown in Figure 2.16. There are two main configurations for quadrotor: "+" configuration as in Figure 2.16a and "X" configuration as in Figure 2.16b. The motors are equidistant from the center of the quad by about $L$.

Each rotor $M_i$ (for $i = 1, \ldots, 4$) generates thrust $f_i$ for $i = 1, \ldots, 4$. The direction of rotation of the rotors are fixed and $f_i$ is always a positive quantity. The main thrust is the sum of all the thrusts which are generated by the rotors. The detailed mathematical equations of quadrotor will be studied in Chapter 3.
Figure 2.15: Multirotors classification according to the principle of flight

In order to avoid the yaw drift due to the reactive torques, the quadrotor aircraft is configured
such that the set of rotors \( M_2, M_4 \) (left-right) revolves in clockwise (CW) direction, while the pair of rotors \( M_1, M_3 \) (front-rear) rotates in counterclockwise (CCW) direction.

Advantages:

- Rotor mechanics are simplified as it depends on four fixed pitch rotors unlike the variable pitch rotor in the helicopter.
- Due to the symmetry in the configuration, the gyroscopic effects are reduced leading to simpler control.
- Stationary hovering can be more stable in quadrotors than in helicopters due to the presence of four propellers providing four thrust forces shifted a fixed distance from the center of gravity instead of only one propeller centered in the middle as in the helicopters structure.
- More advantages are the vertical take-off and landing capabilities, better maneuver-ability and smaller size due to the absence of a tail, these capabilities make quadrotors useful in small area monitoring and buildings exploration.

Disadvantages:

- Quadrotors consume a lot of energy due to the presence of four separate propellers.
- Quadrotors have a large size and heavier than some of their counterparts again to the fact that there is four separate propellers.
Based on the path that has been generated, robots can accomplish their predefined tasks such as cleaning, painting, window cleaning, and inspection of complex structures. CPP has been extensively studied in recent years for applications such as vacuum cleaning robots [245], painter robots [17], path planning for autonomous underwater vehicles [171], demining robots [3], lawn mowers [28]. For the aerial context, the obstacles can be represented by no-flying zones (NFZ) that the UAV should avoid during its operation.

In [36], the authors defined the requirements for the robot to perform a coverage operation. Although the target application for CPP problems in the aforementioned paper is mentioned for mobile robots in a 2-dimensional environment, the same requirements are used for other coverage scenarios as follows:

- the robot is required to go through all the points in the target area covering it completely
2.3. Coverage Path planning methods used for UAV

- the robot is required to fill the region of interest without overlapping paths.
- the robot must operate continuously and sequentially without any repetition of paths
- the robot is required to avoid all the obstacles of the region of interest
- simple motion trajectories such as straight lines or circles should be used for the purpose of simplicity in control
- the use of an 'optimal' path is desired under available conditions

However, due to the complexity of the working region with obstacles, it is really hard to satisfy all the aforementioned requirements. As a result, some requirements need to be made with a higher priority than others.

Region of interest

The region of interest to be completely covered by a robot can be represented by a polygon which contains $n$ vertices $v_1,\ldots,v_n$. Each vertex $v_i$ contains a pair of coordinates $(v_x(i),v_y(i))$, and the internal angle at $i$-th vertex can be referred by $\gamma_i$. The edge between two vertices $v_i$ and $v_{i+1}$ for $i = 1,\ldots,n-1$ are $e_i$ and the edge between vertex $v_n$ and $v_1$ is $e_n$ as in Figure 2.17. The shape of region of interest can be any type of polygon such as convex with no holes inside as in Figure 2.17a, concave with holes inside as in Figure 2.17d. These holes can be considered as the no-fly zones where the UAVs are not allowed to fly.

2.3.1 No Decomposition

If the shape of the region of interest is regular-shaped and non-complex, the complete coverage mission can be performed without decomposition. Simple geometric patterns are sufficient to explore such areas. The two popular patterns are back-and-forth (BF) as in Figure 2.18a and the spiral (SP) as in Figure 2.18b.

![Figure 2.18: Simple geometric patterns for coverage path planning](image-url)
2.3.2 Cellular Decomposition (CD)

The environment is always divided into non-overlapping regions called cells using a decomposition technique in order to simplify the coverage [44]. The size of the cells depends on the type of decomposition method and an applied specific strategy to guarantee complete coverage. These cells typically have the same size as a robot (terrestrial coverage) or are proportional to the sensor’s range (aerial coverage). Several motions are required to fully cover the large cell, while a single motion is enough for the smaller cells. There exist several different cellular decomposition methods, however, the most commonly used in CPP problems involving UAVs are exact and approximate cellular decomposition.

**Exact cellular decomposition**

Exact cellular decomposition is a decomposition method in which the regions of interest are divided into non-overlapping sub-areas (cells) whose reunion exactly occupies the target area. By using a simple motion as back-and-forth, each cell can be fully explored. Consequently, the CPP problem of the whole region of interest is now referred to as the motion planning problem from one cell to another [44]. The robot can move between two cells, which have a mutual border. The adjacency graph is proposed to represent the motion of the robot as in Figure 2.19. In this adjacency graph, each cell represents a node, while the edge represents neighbour cells. The final complete coverage path is the combination of motions performed inside the cells and the connections between cells [80].

Several cellular decomposition methods have been studied as trapezoidal decomposition technique [120], boustrophedon decomposition [45], and Morse-based cellular decomposition [225].

In the trapezoidal decomposition technique [120], the free spaces are divided into trapezoidal cells. There are two parallel sides on each cell, and each cell can be covered by simple back and forth motion parallel to either side. Therefore, the whole working area can be totally
scanned by visiting each cell in the adjacency graph. A vertical line is swept from left to right through the working area of the robot. Each time the line encounters a vertex of a polygon, one can say that an event occurs. Three types of events are defined: IN, OUT, and MIDDLE. In an IN event, the current cell is closed and two new cells are opened. When an OUT event occurs, the current two cells are closed and a new cell is created. Finally, MIDDLE event is the event that a current cell is closed and a new single cell is initiated. Consequently, by using these three events, the environment can be totally divided into separated trapezoidal cells.

A drawback of the trapezoidal decomposition (shown in Figure 2.20a) is that it generates many cells that, intuitively, can be merged together to form bigger cells. This is clearly an inconvenient, as the more cells are present, the longer the final coverage path is. This happens because the trapezoidal decomposition creates only convex cells. However, non-convex cells can also be completely covered by simple motions. To overcome this limitation, the boustrophedon cellular decomposition was proposed. The boustrophedon decomposition (shown in Figure 2.20b) is similar to the trapezoidal decomposition introduced above, but it only considers vertices where a vertical segment can be extended both above and below the vertex. The vertices where this occurs are called critical points.

![Figure 2.20: Exact cellular decomposition method](image)

The boustrophedon decomposition [45] addresses the issue of redundant movements by merging together cells between successive IN and OUT movements. The major difference is in the case of a MIDDLE event, where no new cell is formed, but the current cell is updated in width. So cells are only created on change of connectivity, as a result the number of cells are less than in the case of trapezoidal decomposition. The point which changes the connectivity of the cell is termed as a critical point. In the implementation of this algorithm, the MIDDLE event is replaced by two new events called – FLOOR and CEILING. The FLOOR event corresponds to vertices on top of obstacles, while CEILING event corresponds to vertices that are at the bottom of obstacles. Both an IN event as well as an OUT event are associated with FLOOR and CEILING pointers. So for a given cell, CEILING and FLOOR pointers points to the top and bottom of a cell.

In [225], Acar et al generalized the boustrophedon decomposition by proposing a cellular decomposition approach based on critical points of Morse functions. In this paper, the authors show that the boustrophedon decomposition is a particular case of Morse decomposition. With respect to the original boustrophedon decomposition, the Morse-based decomposition has the advantage of handling also non-polygonal obstacles. By choosing different Morse
functions, different cell shapes are obtained, e.g. circular or spiked cells. Theoretically, Morse-decomposition can be applied to any n-dimensional space. Moreover, they presented a method to perform coverage of planar spaces by detecting the critical points using sensory range information, and a motion-template-based algorithm that ensures to encounter all the critical points in the target area. Therefore, this method allows complete coverage on line.

**Approximate cellular decomposition**

For approximate cellular decomposition technique, the region of interest is divided into a set of regular cells [44]. The shape of regular cells can be a square, rectangular, triangle, or hexagonal. The size of the cells is proportional to the footprint of the camera in the UAV. The coverage path contains a set of \( n \) way-points \( (w_1, \ldots, w_n) \) as in Figure 2.21. Each way-point \( w_i \) contains not only information such as latitude, longitude, and altitude, but also navigation command to the vehicle as take-off, landing, speed, the coordinate of the next point, or the command to move to the next point.

![UAV picture frame](a) UAV picture frame

![Grid and way-points](b) Grid and way-points

**Figure 2.21:** Approximate cellular decomposition method

### 2.4 State of the art on the control of quadcopters

The quadrotor UAV is a great platform for control systems research thanks to its nonlinearities and under-actuated configuration. Consequently, research on quadrotors UAV has attracted a lot of attention from researchers and industrials all over the world in recent years. Thanks to the wide development of modern control theory and technology, many advanced control algorithms have been researched and used successfully for quadrotors controlling.

The quadrotor UAV controllers can be classified into three main categories: (i) linear flight controllers, (ii) model-based nonlinear flight controllers, (iii) learning-based control methods.
2.4. State of the art on the control of quadcopters

2.4.1 Proportional Integral Derivative controller

Proportional Integral Derivative (PID) controller is one of the most successful and widely used among linear controllers. It is indeed the most applied controller in the industry [104]. The classical PID controller has the advantage that it has a simple structure, high stability, good robustness, and parameters are easy to adjust but needs experience.

In [58], a Disturbance Observer Based (DOB) PID controller for a quadrotor testbed has been developed which can stabilize the quadrotor and enhance the performance of the flight control under complex real-time flight scenarios. In [133], the authors propose a linear time-invariant controller consists of a Proportional Derivative (PD) controller and a robust compensator. This controller achieves the robust attitude control for uncertain quadrotors.

Another PID controller [127] is applied for regulating both the position and orientation of a quadrotor. The parameter gains of the controller are chosen manually. Small response time, almost zero steady-state error, and slight overshoot show the performance of the controller for attitude stabilization. In [197] a PID controller that can perform a steady flight of quadrotor from one point to another is designed while ignoring air resistance and external factors. Another Proportional Integral (PI) /PID controller which reduces the steady-state error is proposed in [86]. However, this controller is not reasonable and effective to compensate for Coriolis force.

A nonlinear PID controller is proposed in [211]. The structure of this nonlinear PID controller consists of a linear PID control module and an inertia torque compensation department module. The effectiveness of this controller for attitude stabilization and robustness of the unmodeled dynamic system is shown in the simulation results.

Although the PID controller has been successfully applied for controlling the quadcopter, there exists some disadvantages. The PID controller gains turning is a challenge as it must be conducted around the equilibrium point to give a good performance. Therefore, this is a time-consuming process. In addition, the classic PID controller might not really suit for quadrotor control when it operates in an unstable environment.

2.4.2 Linear Quadratic Regulator (LQR)/Gaussian-LQR/G

The Linear Quadratic Regulator (LQR) is a popular optimal control algorithm and have been successfully used for controlling quadrotors. The LQR operates a dynamic system in the space state form by minimizing a suitable quadratic objective function. By adjusting the system control gain, the LQR controller can adapt each control circuit performance coordinate with system requirements automatically.

The LQR algorithm is applied for quadcopter in [29]. The authors also compare its performance to the performance of PID controller. The two controllers developed on this paper provide average results. However, the conclusion about the better performance of the LQR controller than the PID is not indicated clearly.

In [48], the authors propose a simple path-following LQR controller on a full dynamic model quadrotor. The simulation results show that by using optimal real-time trajectories under the presence of wind and other disturbances, the quadcopter still tracks the predefined path. Nevertheless, the quadcopter loses path tracking after avoiding the obstacles.
However, these algorithms are suitable for linear systems and it is not convenient for nonlinear systems unless some hypotheses are made. In [252], an LQR is proposed for controlling the sensitivity and reaction speed of a quadrotor. The simulation results show that the performance of the linear LQR model is better than the nonlinear model for real-time and speed reaction.

The LQR algorithm becomes Linear Quadratic Gaussian (LQG) when it combines with Kalman Filter. The LQG algorithm is really effective for the systems with Gaussian noise or incomplete state information. In [150], an LQG with integral action is developed for quadrotor attitude stabilization and gives good results in hover mode.

### 2.4.3 Sliding Mode Control (SMC)

SMC is a nonlinear control algorithm that is robust to parameter variations and model uncertainties and is insensitive to external disturbances. SMC uses a discontinuous control signal to the system to make sure that the system slides along a prescribed path. The main advantage of SMC is that it does not simplify the dynamics through linearization and has good tracking. However, the main disadvantage of SMC is the chattering phenomenon.

A PID based sliding mode controller [141] is proposed for a micro quadrotor. This SMC is able to make the micro quadrotor accurately track the desired altitude and attitude. In [243], the quadrotor system was subdivided into the full-actuated and under-actuated systems. An SMC is designed for stabilizing the cascaded under-actuated systems. Simulation results show the robustness and good stability of the quadcopter.

In [53], a Super Twisting Algorithm (STA) based on the second-order slinging mode technique is designed and implemented for attitude tracking of the quadrotor. The good performance of the proposed method in stabilization, reference tracking, and disturbance rejection cases are shown in experimental results. Beside, in [194], the authors propose a sliding mode controller based on the Lyapunov stability theory. The proposed SMC controller gains the ability to track the predefined path and drive the quadrotor to the desired position while injecting noises. An SMC controller is designed in [24] that improves the robustness to the external disturbances and model uncertainty of the system. This proposed SMC does not require to resort to high power gain and is able quickly to compensate for the changes of the external disturbances.

### 2.4.4 Backstepping Control

Backstepping control is a recursive algorithm that decomposes the controller into several steps and makes each step stable progressively. The advantage of backstepping control is that this algorithm converges fast thanks to less computational resources and it has the ability to reject disturbances well. However, its disadvantage is that its robustness is not good in the presence of modeling uncertainties.

A DOB based backstepping controller in [59] is designed for high-performance trajectory tracking of the quadrotor. This disturbance observer-based controller serves as a compensator, which effectively rejects external disturbances and model mismatches. In [142], the quadrotor system is divided into under-actuated, fully actuated, and propeller subsystems. Then, a backstepping control is designed for stabilizing the quadcopter. The simulation
results show that good tracking was achieved for position and yaw angle. The roll and pitch angles are stabilized by using the Lyapunov stability theory.

Besides, a nonlinear controller using Lyapunov-based backstepping techniques for path following of quadrotor is designed in [35]. The controller in this approach guarantees the global convergence of the closed-loop path following error to zero under the presence of constant wind disturbances.

In [71], an integrator is added and the traditional backstepping algorithm becomes integral backstepping control for increasing the robustness of the general backstepping controller for a quadcopter under external disturbances. The integrator in this integral backstepping controller is able to eliminate the steady-state errors of the system, reduces response time and restrains the overshoot of the control parameters.

2.4.5 Adaptive Control Algorithms

Adaptive control is a robust control technique which is aimed at adapting to parameter changes in the system to obtain the optimal control effect during operating time. The parameters are either uncertain or time-varying. Adaptation means a combination of online parameter estimation and control, whereby an appropriate controller is selected on the knowledge of the current estimate for the uncertain process.

In [54], a continuous time-varying adaptive controller is developed for quadcopter with known uncertainties in mass, moments of inertia, and aerodynamic damping coefficients. A decentralized adaptive controller is presented in [151]. This controller is designed with the improved Lyapunov based Model Reference Adaptive Control technique. Simulation results show the proposed controller works properly for a quadrotor with parametric and non-parametric uncertainties under various conditions during flight time.

2.4.6 Robust Control Algorithms

A robust controller is designed to deal with uncertainty in the system parameters or disturbances. This controller ensures the controller performance within acceptable disturbance ranges or un-modeled system parameters. The main disadvantage of the robust controller is poor tracking ability.

In [134], the authors develop a robust motion controller based on a nominal controller and robust compensator for attitude and position control of a quadrotor. The proposed robust compensator minimizes the influence of uncertainties, such as nonlinear dynamics, coupling, parametric uncertainties, and external disturbances in the rotational and translational dynamics.

Another robust tracking controller is designed in [221]. This controller guarantees asymptotic stability under the presence of parametric uncertainties and unknown nonlinear disturbances.

2.4.7 Optimal Control Algorithms

Several optimal controllers have been successfully applied for controlling the quadcopter, such as LQR, $L_1$, $H_{\infty}$, and Kalman filter. The main disadvantage of optimal control is generally their poor robustness. An optimal controller for reference tracking of both attitude
and heading of a quadcopter which is robust and $L_1$ optimal is proposed in [201]. The performance of the controller for error minimization and rejection of persistent disturbances is validated by the experiment.

In [186], the authors design an integral optimal predictive $H_\infty$ controller for stabilization of the rotational movement of a quadrotor and for path following. The simulation shows that the controller has good robustness and is able to reject the external disturbances.

Another $H_\infty$ controller is designed in [42] which is based on quasi-LPV. This controller can perform the quadrotor control of vertical speed and attitude. The loop shaping $H_\infty$ is developed to combine robust control and classic loop shaping, which overcome the usual drawbacks of the standard $H_\infty$. Some other $H_\infty$ controller for quadcopter are also shown in [188] and [70].

### 2.4.8 Model Predictive Control (MPC)

MPC is a type of control that uses an explicit model of the plant to predict future output behavior while minimize the tracking error of future horizon by solving optimal control problems online [114]. The main advantage of MPC compared to Backstepping, feedback linearization, and also sliding mode, is that this controller is able to handle operational constraints prevalent in a control system explicitly. However, a typical disadvantage of MPC is the need for high computational power due to repetitive calculations online.

In [2], an efficient MPC was successfully implemented which deploys fewer prediction points and the less computational requirement is presented in order to control a quadrotor with limited airborne computational power.

### 2.4.9 Exact Feedback Linearization

Feedback linearization is a process of converting exactly, by nonlinear state or output feedback control a nonlinear system into a linear system so that the linear feedback control techniques can be applied. After that, the controller is designed by theory related to the linear control system to achieve the requirements of controlling the system. The main disadvantage of exact feedback linearization is the need of an exact model. This leads to the complexity in controller design.

In [154], the quadcopter dynamic is divided into the inner loop (for attitude) and the outer loop (for position). The authors ignore some factors such as air resistance and design feedback linearization controller to control the attitude of the quadcopter. Besides, the combination of feedback linearization and $GH_\infty$ controllers are applied to design the controller for a quadcopter. This controller takes into account also the parameter uncertainties, noises, and external disturbances. Consequently, the designed controller gains a high quality of robustness.
2.5 Conclusion

In this chapter, a short review of UAVs, their classifications, applications, and advantages and disadvantages has been analyzed. Then, the state of the art of complete Coverage Path Planning (CPP) of UAVs and control of quadrotors are also reviewed.
This chapter is dedicated to system modeling of quadrotor. In section 3.1, we offer a brief review of the previous methods for modeling the quadrotor. Then the concepts and generalities for writing the dynamic model of the quadrotor are given in the section 3.2. Next, the quadrotor kinematic is described in section 3.3. The knowledge about the forces and moments acting on the quadrotor is required for building the dynamic system differential equations of quadrotor. Therefore, the forces and moments acting on the quadrotor are discussed in section 3.4. Then, we get the dynamic model of the quadrotor by using the Euler-Lagrange formalism in section 3.5. The chapter concludes with small conclusion.
3.1 Review of the multirotors modeling

Since there are 6 degrees of freedom (DOF) but controlled by only 4 input variables (the speeds of four propellers), the quadcopters are underactuated, highly dynamic, nonlinear, and coupled systems. In addition, the uncertainties, caused by the environment and induced by aerodynamic phenomena, lead to challenging modeling task. By using a number of assumptions, the factors that are too small and that have a negligible influence on quadcopters dynamics can be ignored. These simplified models can be used to approximate the vehicle dynamics requiring effective control strategies. Many models have been studied in the literature, with various levels of complexity and completeness.

Mesicopter project [72], started in 1999 and ended in 2001. It aimed to study the feasibility of a centimeter scale quadrotor. In this paper, the author derived a dynamic model for a small quadrotor called Mesicopter. The Mesicopter was the first proposed quadrotor model that is used for hovering. The Mesicopter model was generated by assuming that the dynamics are decoupled along the two planes of symmetry. The author has also explicitly given the expression of some aerodynamic forces such as thrust and hub.

In [62], the authors proposed a dynamic model for X-shaped quadrotor. In this paper, the attitude dynamics are modeled by double integrators and ZYX-Euler angles representation was used for describing the rotations of the quadcopter in the East-North-Up (ENU) standard of frames. Beside, a compact quadcopter model was proposed in [213]. The equations of motion of quadcopter were considered in the North-East-Down (NED) reference frame by using Newton’s equations of motion of a rigid object. Several aerodynamic forces and moments are neglected such as the drag force were assumed in this model.

In [216], the author took into account the gyroscopic effect due to the rotation of propellers considered as rigid rotating disks. In [179], an extended model of the quadrotor is used by adding the dynamics of the rotor to the motion equation of the quadrotors. The authors related the applied inputs to the angular velocities of the rotors. The dynamics of the rotor are approximated by a first-order system. Then for control purposes, The final model of the quadrotor is simplified.

In [61], the drag forces that affect the translational dynamics were added to the equations of motion of the quadrotors. These forces were considered as functions of the velocities. The same model was also derived by using the Euler-Lagrange approach as in [167].

In the PhD thesis of Bouabdallah in [30] and in his paper [195], the dynamic model of a cross quadrotor was studied. This model included also the blade flapping effect. In this thesis, both Euler-Lagrange and Newton-Euler approaches are used for the modeling dynamic model of the quadcopter. However, the various effects are not well defined in the appropriate frames, which lead to some errors that are reported and rectified later in the thesis of Wang in [232].

Hoffmann’s work in [79] showed that the flapping tips the thrust vector away from the horizontal plane. As a result, some residual forces influence attitude control as well as the total thrust force. After that, this phenomenon has been more extensively studied in [189]. Other aspects such as the non-rigidity of propellers [177], the ground effect [126] [20], etc have also been further studied more.
In this chapter, we propose a dynamic model of the quadcopter based on Wang’s model under the ideal flight conditions (i.e. without wind). In our model, we consider the effect of the hub forces as well as the hub moment around $Z_B$-axis.

### 3.2 Concepts and Generalities

The Euler angles are the three angles provided by Leonhard Euler and are the basis of a method to represent the 3D orientation of an object with respect to a fixed coordinate system using a combination of three rotations around different axes. The reference frames used for describing the Euler angles are Inertial frame, Vehicle 1 frame, Vehicle 2 frame and body-fixed frame. The inertial frame axes are Earth-fixed, the body frame axes are aligned with the sensor, while the Vehicle-1 and Vehicle-2 are intermediary frames on the sequence of transform operations the inertial frame to the body frame.

#### The Inertial Frame

The inertial frame $R_E (O_E, X_E, Y_E, Z_E)$ as shown in Figure 3.1 is an Earth-fixed set of axes that is used as an unmoving reference.

The sequence of rotations used to represent a given orientation is first yaw, then pitch, and finally roll.

![Figure 3.1: Inertial Frame](image1.png) ![Figure 3.2: Vehicle-1 Frame](image2.png) ![Figure 3.3: Vehicle-2 Frame](image3.png) ![Figure 3.4: Body fixed Frame](image4.png)

The Vehicle-1 Frame (Yaw Rotation)

Yaw is the angle represents rotation about the inertial-frame $O_E Z_E$-axis by an angle $\psi$. The yaw rotation produces a new coordinate frame $R_1 (O_1, X_1, Y_1, Z_1)$ where the $O_1 Z_1$-axis is aligned with the inertial frame and the $x$ and $y$ axes are rotated by the yaw angle $\psi$. The new coordinate frame $R_1 (O_1, X_1, Y_1, Z_1)$ is called vehicle-1 frame and shown in Figure 3.2.

Rotation of a vector from the Inertial Frame $R_E$ to the Vehicle-1 Frame $R_1$ can be performed by multiplying the vector by the rotation matrix

$$R^{v1}_I (\psi) = \begin{bmatrix}
\cos \psi & \sin \psi & 0 \\
-\sin \psi & \cos \psi & 0 \\
0 & 0 & 1
\end{bmatrix} \tag{3.1}$$
The Vehicle-2 Frame (Yaw and Pitch Rotation)

The pitch angle quantifies the rotation of the vehicle 1 frame around the vehicle-1 frame $O_1Y_1$-axis by an angle $\theta$. The pitch rotation produces a new coordinate frame $R_2(O_2, X_2, Y_2, Z_2)$ where the $O_2Y_2$-axis is aligned with the vehicle-1 $O_1Y_1$-axis and the $x$ and $z$ axes are rotated by the yaw angle $\theta$. The new coordinate frame $R_2(O_2, X_2, Y_2, Z_2)$ is called vehicle-2 frame and shown in Figure 3.3. It is important to note that pitch is not rotation about the inertial-frame $O_EY_E$-axis.

The rotation matrix for moving from the vehicle-1 frame $R_1$ to the vehicle-2 frame $R_2$ is given by

$$R_{v2}^{v1}(\theta) = \begin{bmatrix} \cos \theta & 0 & -\sin \theta \\ 0 & 1 & 0 \\ \sin \theta & 0 & \cos \theta \end{bmatrix} \quad (3.2)$$

The rotation matrix for moving from the inertial frame $R_E$ to the vehicle-2 frame $R_2$ is the multiplication of the yaw matrix and the pitch matrix:

$$R_{v2}^{v2}(\theta, \psi) = R_{v1}^{v2}(\theta) R_{v2}^{v1}(\psi) \quad (3.3)$$

![Figure 3.5: The Inertial Frame to Body frame](image)

The Body Frame (Yaw, Pitch, and Roll Rotation)

The body reference frame $R_B(O_B, X_B, Y_B, Z_B)$ is produced from the rotation vehicle-2 frame $R_2$ about the vehicle-2 $O_2X_2$-axis by an angle $\phi$ as shown in Figure 3.4. The body frame is the coordinate system that is aligned with the body of the aircraft as in Figure 3.5. For the quadcopter, the body-frame $O_BX_B$-axis is the axis that passes from the center of the quadcopter $O_B$ to the first motor, while the body-frame $O_BY_B$-axis is the axis that passes from the center of the quadcopter $O_B$ to the fourth motor.
The rotation matrix for moving from the vehicle-2 $R_2$ frame to the body frame $R_B$ is given by
\[
R^B_{v2}(\varphi) = \begin{bmatrix}
1 & 0 & 0 \\
0 & \cos \varphi & -\sin \varphi \\
0 & \sin \varphi & \cos \varphi
\end{bmatrix}
\] (3.4)

Consequently, the complete rotation matrix for moving from the inertial frame $R_E$ to the body frame $R_B$ is given by
\[
R^B_I(\varphi, \theta, \psi) = R^B_{v2}(\varphi) R^2_{v1}(\theta) R^v1(\psi)
\] (3.5)

Performing the multiplication, the complete rotation from the inertial frame $R_E$ to the body frame $R_B$ is given by
\[
R^B_I(\varphi, \theta, \psi) = R^B_{v2}(\varphi) R^2_{v1}(\theta) R^v1(\psi)
\] (3.6)

The rotation matrix for moving the opposite direction from the body frame $R_B$ to the inertial frame $R_E$ is given by
\[
R^I_B(\varphi, \theta, \psi) = R^v1(-\psi) R^2_{v1}(-\theta) R^v2_{v1}(\varphi)
\] (3.7)

Performing the multiplication, the complete rotation from the body frame $R_B$ to the inertial frame $R_E$ is given by
\[
R^I_B(\varphi, \theta, \psi) = R(x, \varphi) R(y, \theta) R(z, \psi)
\]
\[
= \begin{bmatrix}
\cos \psi \cos \theta & \cos \theta \sin \psi & -\sin \theta \\
\cos \psi \sin \varphi \sin \theta - \cos \varphi \sin \psi & \cos \varphi \cos \psi + \sin \varphi \sin \theta \sin \psi & \sin \varphi \sin \theta \\
\sin \varphi \sin \psi + \cos \varphi \cos \psi \sin \theta & \cos \varphi \cos \psi \sin \theta \cos \varphi - \cos \psi \sin \varphi & \cos \varphi \cos \theta
\end{bmatrix}
\] (3.8)

Note that all this is reverse the order of operations and reverse the direction of rotation.

**Remark 3.1.** The Euler angles $\phi$, $\theta$, and $\psi$ are bounded as follows
\[
-\frac{\pi}{2} \leq \varphi \leq \frac{\pi}{2} \\
-\frac{\pi}{2} \leq \theta \leq \frac{\pi}{2} \\
-\pi \leq \psi \leq \pi
\] (3.9)

Based on the previous description, the transformation between the Earth-fixed frame and the Body-fixed frame can be explicitly expressed using the rotation matrix $R$. So, the velocity vector $V^B = \begin{bmatrix} u & v & w \end{bmatrix}^T \in \mathbb{R}^3$ of the vehicle, expressed in a Body-fixed frame, can be rotated into the Earth-fixed frame as follows
\[
\dot{\xi} = \begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} = \begin{bmatrix}
c_\theta c_\psi & s_\theta s_\psi c_\psi - c_\varphi s_\psi & c_\varphi s_\theta c_\psi + s_\varphi s_\psi \\
c_\theta s_\psi & s_\theta s_\psi s_\psi + c_\varphi c_\psi & c_\varphi s_\theta s_\psi - s_\varphi c_\psi \\
-s_\theta & c_\theta c_\psi & c_\varphi c_\theta
\end{bmatrix} \begin{bmatrix}
u \\
v \\
w
\end{bmatrix}
\] (3.10)

where $\dot{\xi} = \begin{bmatrix} \dot{x} & \dot{y} & \dot{z} \end{bmatrix}^T \in \mathbb{R}^3$ is the velocity vector of the quadrotor in the Earth fixed frame $R_E$. $c_*$ denotes $\cos*$ and $s_*$ denotes $\sin*$.
### 3.2.1 Quadcopter model

A quadcopter is a helicopter that consists of a rigid cross-frame equipped with four rotors \( M_1, M_2, M_3, \) and \( M_4 \) which rotate at angular speed \( \omega_1, \omega_2, \omega_3, \) and \( \omega_4 \) respectively as shown in Fig. 3.6. Each rotor \( M_i \) (for \( i = 1, \ldots, 4 \)) generates thrust \( f_i \) which is proportional to the square of the angular speed \( \omega_i \), means that \( T_i = k\omega_i^2 \). The direction of rotation of the rotors are fixed (i.e., \( \omega_i \geq 0, i \in \{1, 2, 3, 4\} \)), consequently \( T_i \) is always a positive quantity.

The main thrust \( u \) is the sum of all the thrusts which are generated by the rotors, that is

\[
u = \sum_{i=1}^{4} T_i
\]  

(3.11)

![Figure 3.6: Quadcopter configuration with coordinate frames and forces](image_url)

In order to avoid the yaw drift due to the reactive torques, the quadrotor aircraft is configured such that the set of rotors \( M_2, M_4 \) (left-right) revolves at angular speeds \( \omega_1 \) and \( \omega_2 \) in clockwise (CW) direction generating thrusts of \( T_1 \) and \( T_3 \), while the pair of rotors \( M_1, M_3 \) (front-rear) rotates at angular speeds \( \omega_2 \) and \( \omega_4 \) in counterclockwise (CCW) direction generating thrusts of \( T_2 \) and \( T_4 \).
The quadcopter is controlled by varying the angular speeds $\omega_i, i = 1, 2, 3, 4$ of the four rotors $M_i, i = 1, 2, 3, 4$. The forward/backward, left/right, and the yaw motions are achieved through a differential control strategy of the thrust generated by each rotor.

Forward pitch motion is obtained by increasing the speed of the rear motor $M_3$ while reducing the speed of the front motor $M_1$ as in Figure 3.8. Contrary, backward pitch motion is obtained by reducing the speed of the rear motor $M_3$ while increasing the speed of the front
motor $M_1$. Similarly, the roll right motion is obtained by increasing the speed of the left motor $M_2$ while reducing the speed of the right motor $M_4$ as in Figure 3.7. Contrary, the roll left motion is obtained by reducing the speed of the left motor $M_2$ while increasing the speed of the right motor $M_4$. Yaw motion is obtained by increasing the torque of the front and rear motors ($\tau_1$ and $\tau_3$) while decreasing the torque of the lateral motors ($\tau_2$ and $\tau_4$) as in Figure 3.9 or inverse. Such motions can be performed while maintaining the total thrust constant.

The hovering motion is obtained by maintaining constant speed for all the motors such that the total thrust is equal to $mg$ as in Figure 3.10 while compensating disturbances.

The $Z$ motion is obtained by maintaining the same speed for all the motors. The quadrotor moves up if the total thrust is greater than $mg$ as in Figure 3.11 and moves down if the total thrust is less than weight $mg$.

\[ \begin{pmatrix} v_x \\ v_y \\ v_z \end{pmatrix} ; \quad \Omega = \begin{pmatrix} p \\ q \\ r \end{pmatrix} \]
The relationship between the angular velocity vector in the body frame and the generalized velocities $\dot{\eta}$ is depicted as

$$\Omega = W_\eta \dot{\eta}$$

$$\dot{\eta} = W^{-1}_\eta \Omega$$

(3.14)

where

$$W_\eta = \begin{bmatrix}
1 & 0 & -\sin \theta \\
0 & \cos \varphi & \cos \theta \sin \varphi \\
0 & -\sin \varphi & \cos \theta \cos \varphi
\end{bmatrix}$$

(3.15a)

$$W^{-1}_\eta = \begin{bmatrix}
1 & \sin \varphi \tan \theta & \cos \varphi \tan \theta \\
0 & \cos \varphi & -\sin \varphi \\
0 & \sin \varphi / \cos \theta & \cos \varphi / \cos \theta
\end{bmatrix}$$

(3.15b)

\begin{remark}
The matrix $W_\eta$ is invertible if

$$\theta \neq (2k - 1) \pi / 2, k \in \mathbb{Z}$$

\end{remark}

The quadrotor is assumed to have symmetric structure with the four arms aligned with the body $x$- and $y$-axes. Thus, the inertia matrix is diagonal matrix $I$ in which

$$I = \begin{bmatrix}
I_x & 0 & 0 \\
0 & I_y & 0 \\
0 & 0 & I_z
\end{bmatrix}$$

(3.16)

where $I_x$, $I_y$, and $I_z$ are the moments of inertia with respect to the axis $x$, $y$, and $z$ respectively.

### 3.4 Applied forces and moments on the quadcopter

#### 3.4.1 Applied forces

The ground effects are neglected, then three main forces acting on the quadcopter are considered: gravity force, thrust forces, and hub forces.

- **Gravity**: Gravity is the force by which a planet or other body draws objects toward its center and denoted as

$$G = -mg$$

(3.17)

Gravity is along the axis $Z_E$ in the negative direction with $g$ is the gravity acceleration.

- **Thrust**: Each rotor $r_i$ produces the thrust $T_i$ which depends on its angular velocity $\Omega_i$. The thrust force $T_i$ is along the $Z_B$ axis in the positive direction. Thrust $T_i$ is depicted in Figure 3.12a. The equation for thrust is

$$T_i = C_T \rho A (\Omega_i R_r)^2$$

(3.18)

where $C_T$ is the aerodynamic coefficient, $\rho = 1.293 kg/m^3$ is the air density, $A$ is the effective propeller disk area, $R_r$ is the propeller radius.
• **Hub forces**: Each rotor \( r_i \) also produces the hub force \( H_i \) which is also dependent on its angular velocity \( \Omega_i \). The hub force \( H_i \) is in the plane \( X_B Y_B \) on the negative direction of the horizontal velocity \( V_h \) (the projection of the forwarding velocity \( V_f \) in the \( X_B Y_B \) plane). Thus, the hub force can be decomposed into two components \( H_{xi} \) along \( X_B \)-axis and \( H_{yi} \) along \( Y_B \)-axis in the Body-fixed frame. The Hub force \( H_i \) and its two components \( H_{xi} \) and \( H_{yi} \) are depicted in Figure 3.12a. The equation for hub force is

\[
H_i = C_H \rho A (\Omega_i R_e)^2
\]

where \( C_H \) is the aerodynamic coefficient.

Thus, the total thrust force \( T \), and hub forces \( H_{xi}, H_{yi} \) on \( x \) and \( y \) axes acted on the quadcopter can be calculated as

\[
T = \sum_{i=1}^{4} T_i
\]

\[
H_x = \sum_{i=1}^{4} H_{xi}
\]

\[
H_y = \sum_{i=1}^{4} H_{yi}
\]

Once the main forces have been reviewed, the net external force vector acting on the vehicle is expressed in the Body-fixed frame as:

\[
F^B = \begin{bmatrix}
H_x \\
H_y \\
T
\end{bmatrix} + R^B_T \begin{bmatrix}
0 \\
0 \\
G
\end{bmatrix}
\]

\[
= \begin{bmatrix}
- \sum_{i=1}^{4} H_{xi} \\
- \sum_{i=1}^{4} H_{yi} \\
\sum_{i=1}^{4} T_i
\end{bmatrix} + R^B_T \begin{bmatrix}
0 \\
0 \\
-mg
\end{bmatrix}
\]

where \( R^B_T \) is the rotation matrix from the Earth-fixed frame \( R_E \) to the Body-fixed frame \( R_B \) as defined on 3.6.
3.4.2 Applied moments

In this section, the main external moments that are expressed in the Body-fixed frame and their directions will be presented.

- **Rolling and Pitching moments**: Roll moments $M_\phi$ around $X_B$ and pitch moment $M_\theta$ around $Y_B$ axes, are achieved by the difference in combined thrusts in the opposite sides of the vehicle. These moments are really important because they contribute to the control of the vehicle. The directions of these moments are decided according to the right hand rule. The Roll moments $M_\phi$ and pitch moment $M_\theta$ can be defined as

$$M_\phi = L \sum_{i=1}^{4} \sin \alpha_i T_i$$
$$M_\theta = -L \sum_{i=1}^{4} \cos \alpha_i T_i$$

\[ (3.24) \]

where $\alpha_i$ denotes the angle between the $i$-th arm and $X_B$-axis.

- **Yawing moment**: Moment $Q_i$ around the shaft of the $i$-th rotor is generated by the acting of the aerodynamic forces on the blade elements. Thus the yawing moment $Q_i$ for each rotor is defined as:

$$Q_i = C_Q \rho A R_r (\Omega_i R_r)^2$$

\[ (3.25) \]

where $C_Q$ is the aerodynamic coefficient.

The sum of these moments, considering all the rotors, induces the rotation of the quadrotor about $Z_B$ axis. There are 4 rotors that are separated by different rotational directions (clockwise and counterclockwise) inducing moments in the different direction. Consequently, the total yawing moment is given by:

$$Q = \sum_{i=1}^{4} S_{pi} Q_i$$

\[ (3.26) \]

where $S_{pi} = 1$ if $i$-th rotor rotates in the clockwise direction and $S_{pi} = -1$ if $i$-th rotor rotates in the counter clockwise direction.

- **Hub moment**: As we have seen above, the hub force has two components $H_x$ and $H_y$ along $X_B$ and $Y_B$ axes respectively. These hub forces generate moments on the vehicle around the $Z_B$-axis. These two components contribute to the motion according to their locations $o_i, i = 1, ..., 2N_r$, and can be defined as.

$$H_x = L \sum_{i=1}^{4} \sin \alpha_i H_{xi}$$
$$H_y = -L \sum_{i=1}^{4} \cos \alpha_i H_{yi}$$

\[ (3.27) \]

Therefore, the resulting hub moment is the sum of the moment of the two component $H_x$ and $H_y$, given by the following equation

$$H = H_x + H_y$$
$$= L \sum_{i=1}^{4} \sin \alpha_i H_{xi} - L \sum_{i=1}^{4} \cos \alpha_i H_{yi}$$

\[ (3.28) \]

where the moment $H_x$ is generated by the force $H_x$ and the moment $H_y$ is generated by the force $H_y$. 
• **Gyroscopic moment**: Rotations about two axes causes a third rotation about a third axis, which is perpendicular to the plane formed by the two former axes (Figure 3.12b). This effect is called the gyroscopic effect. Consequently, when the quadrotor rotates along the $X_B$ axis, another moment along $Y_B$ axis is generated on each spinning rotor. When the quadrotor rotates along $Y_B$ axis, each rotor also has a moment along $X_B$ axis. The direction of moments follows right hand rule. Therefore, the total gyroscopic components can be calculated as:

$$G_x = J_r q \sum_{i=1}^{4} S_{p_i} \Omega_i$$

$$G_y = -J_r p \sum_{i=1}^{4} S_{p_i} \Omega_i$$

(3.29)

where $J_r$ is the moment of inertia of the rotor (consider the moments of inertia of all the rotor are equal), $S_{p_i} = 1$ if $i$-th rotor rotates in the clockwise direction and $S_{p_i} = -1$ if $i$-th rotor rotates in the counter clockwise direction.

• **Blade flapping moment**: When the quadrotor is in the translational flight mode, there exists a difference in lift between the blades that advance and the blades that recede. This effect is called the blade flapping. The difference of the lifts generates a moment to the rotor disk as shown in Figure 3.12c). The flapping moment $B_i$ is around an axis perpendicular to the plane formed by the rotor shaft and the forward velocity of the multirotor and is given by the following equation:

$$B_i = C_B \rho A R_r (\Omega_r R_r)^2$$

(3.30)

where $C_B$ is the aerodynamic coefficient.

The flapping moment $B_i$ of each $i$-th rotor can be separated into two components $B_{x_i}$ and $B_{y_i}$ with respect to the $x$ and $y$ axes. Therefore, the total blade flapping moment of a quadrotor is:

$$B_x = \sum_{i=1}^{4} S_{p_i} B_{x_i}$$

$$B_y = \sum_{i=1}^{4} S_{p_i} B_{y_i}$$

(3.31)

where $S_{p_i} = 1$ if the $i$-th rotor rotates in the clockwise direction and $S_{p_i} = -1$ if the $i$-th rotor rotates in the counter clockwise direction.

Based on the moments affecting the quadcopter as previously seen in (3.24), (3.25), (3.28), (3.29), (3.31), the total moment vector affecting the quadcopter is presented in the Body-fixed frame as:

$$\mathbf{M}^B = \begin{bmatrix}
\mathcal{M}_x + G_x + B_x \\
\mathcal{M}_y + G_y + B_y \\
Q + H \\
l \sum_{i=1}^{4} \sin \alpha_i T_i + J_r q \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{x_i} \\
-l \sum_{i=1}^{4} \cos \alpha_i T_i - J_r p \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{y_i} \\
\sum_{i=1}^{4} S_{p_i} Q_i + l \sum_{i=1}^{4} \sin \alpha_i H_{x_i} - l \sum_{i=1}^{4} \cos \alpha_i H_{y_i}
\end{bmatrix}$$

(3.32)
### 3.5 Modeling with Euler-Lagrange Formalism

Define the Lagrangian \( L(q, \dot{q}) \) as the sum of the translational and rotational energies minus potential energy

\[
L(q, \dot{q}) = T_{\text{trans}} + T_{\text{rot}} - U
\]

where \( T_{\text{trans}} \), \( T_{\text{rot}} \), and \( U \) are the translational kinetic energy, rotational kinetic energy, and potential energy respectively and expressed by the following equations

\[
T_{\text{trans}} = \frac{m}{2} \dot{\xi}^T \dot{\xi}
\]

\[
T_{\text{rot}} = \frac{1}{2} \Omega^T \Omega
\]

\[
U = mgz
\]

where \( z \) is the altitude, \( m \) is the mass, \( \Omega = \begin{bmatrix} p & q & r \end{bmatrix}^T \) is the vector of angular velocity, and \( I \) denotes the inertia matrix of the quadcopter, and \( g \) is the gravity acceleration.

Define the Jacobian matrix \( J(\eta) \)

\[
J = J(\eta) = W^T_\eta IW_\eta
\]

\[
J = \begin{bmatrix}
I_x & 0 & -I_x \sin \theta \\
0 & I_y \cos^2 \varphi + I_z \sin^2 \varphi & (I_y - I_z) \sin \varphi \cos \varphi \cos \theta \\
-I_x \sin \theta & (I_y - I_z) \sin \varphi \cos \varphi \cos \theta & I_x \sin^2 \theta + I_y \sin^2 \varphi \cos^2 \theta + I_z \cos^2 \varphi \cos^2 \theta
\end{bmatrix}
\]

From (3.34b), (3.14), and (3.35) one obtains

\[
T_{\text{rot}} = \frac{1}{2} \dot{\eta}^T J \dot{\eta}
\]

The full dynamic model of quadcopter can be obtained by using Euler-Lagrange equations with external forces as

\[
\frac{d}{dt} \left( \frac{\partial L}{\partial \dot{q}} \right) - \frac{\partial L}{\partial q} = \begin{bmatrix} F_\xi \\ \tau \end{bmatrix}
\]

where \( F_\xi = R(\varphi, \theta, \psi) \hat{F} \in \mathbb{R}^3 \) is the translational force acting on the quadcopter, and \( \tau \in \mathbb{R}^3 \) are the yaw, pitch and roll moments around axis \( z, y, \) and \( x \), the \( R(\varphi, \theta, \psi) \in SO(3) \) is the rotational matrix in (3.8).

From (3.23), one can see that the force \( \hat{F} \) can be written as

\[
\hat{F} = \begin{bmatrix}
-\frac{4}{i=1} H_{xi} \\
-\frac{4}{i=1} H_{yi} \\
\frac{4}{i=1} T_i
\end{bmatrix} + R_B^B \begin{bmatrix} 0 \\ 0 \\ G \end{bmatrix}
\]
Consequently, the translational and rotational Lagrangians are defined respectively as

\[
\begin{align*}
L_{\text{trans}} &= \frac{m}{2} \dot{\xi}^T \dot{\xi} - mgz \\
L_{\text{rot}} &= \frac{1}{2} \dot{\eta}^T J \dot{\eta}
\end{align*}
\] (3.40a, 3.40b)

The derivative of the translational Lagrangian is

\[
\frac{d}{dt} \left( \frac{\partial L_{\text{trans}}}{\partial \dot{\xi}} \right) - \frac{\partial L_{\text{trans}}}{\partial \xi} = F_{\dot{\xi}}
\] (3.41)

gives the following translational equation

\[
m\ddot{\xi} + mgE_z = F_{\dot{\xi}}
\] (3.42)

The derivative of the rotational Lagrangian is given by

\[
\frac{d}{dt} \left( \frac{\partial L_{\text{rot}}}{\partial \dot{\eta}} \right) - \frac{\partial L_{\text{rot}}}{\partial \eta} = \tau
\] (3.43)

\[
\frac{\partial L_{\text{rot}}}{\partial \dot{\eta}} = \frac{1}{2} \left( J + J^T \right) \dot{\eta} = J \ddot{\eta}
\] (3.44)

\[
J \ddot{\eta} + \left( J - \frac{1}{2} \frac{\partial}{\partial \eta} (\dot{\eta}^T J) \right) \dot{\eta} = \tau
\] (3.45)

\[
C(\eta, \ddot{\eta}) = J - \frac{1}{2} \frac{\partial}{\partial \eta} (\dot{\eta}^T J)
\] (3.46)

where

\[
\tau = M^B = \begin{bmatrix}
\sum_{i=1}^{4} l \sin \alpha_i T_i + J_r q \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{x_i} \\
-\sum_{i=1}^{4} l \cos \alpha_i T_i - J_r p \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{y_i} \\
\sum_{i=1}^{4} S_{p_i} Q_i + l \sum_{i=1}^{4} \sin \alpha_i H_{x_i} - l \sum_{i=1}^{4} \cos \alpha_i H_{y_i}
\end{bmatrix}
\] (3.47)

\[
J \ddot{\eta} + C(\eta, \ddot{\eta}) = \tau
\] (3.48)

with \( C(\eta, \ddot{\eta}) \) defined as follows

\[
C(\eta, \ddot{\eta}) = \begin{bmatrix}
c_{11} & c_{12} & c_{13} \\
c_{21} & c_{22} & c_{23} \\
c_{31} & c_{32} & c_{33}
\end{bmatrix}
\] (3.49)
where
\[ c_{11} = 0 \]
\[ c_{12} = (I_y - I_z) \left( \dot{\theta} \cos \varphi \sin \varphi + \dot{\psi} \sin^2 \varphi \cos \theta \right) + (I_z - I_y) \dot{\psi} \cos^2 \varphi \cos \theta - I_x \dot{\psi} \cos \theta \]
\[ c_{13} = (I_z - I_y) \dot{\psi} \cos \varphi \sin \varphi \cos^2 \theta \]
\[ c_{21} = (I_z - I_y) \left( \dot{\theta} \cos \varphi \sin \varphi + \dot{\psi} \sin^2 \varphi \cos \theta \right) + (I_y - I_z) \dot{\psi} \cos^2 \varphi \cos \theta + I_x \dot{\psi} \cos \theta \]
\[ c_{22} = (I_z - I_y) \dot{\psi} \cos \varphi \sin \varphi \]
\[ c_{23} = -I_x \dot{\psi} \sin \theta \cos \theta + I_y \dot{\psi} \sin^2 \varphi \cos \theta \sin \theta + I_z \dot{\psi} \cos^2 \varphi \sin \theta \cos \varphi \]
\[ c_{31} = (I_y - I_z) \dot{\psi} \cos \varphi \sin \varphi \cos^2 \theta - I_x \dot{\psi} \cos \theta \]
\[ c_{32} = (I_z - I_y) \left( \dot{\theta} \cos \varphi \sin \theta + \dot{\psi} \sin^2 \varphi \cos \theta \right) + (I_y - I_z) \dot{\psi} \cos^2 \varphi \cos \theta \]
\[ + I_x \dot{\psi} \cos \theta \sin \theta - I_y \dot{\psi} \sin^2 \varphi \cos \theta \sin \theta - I_z \dot{\psi} \cos^2 \varphi \cos \theta \sin \theta \]
\[ c_{33} = (I_y - I_z) \dot{\psi} \cos \varphi \sin \varphi \cos^2 \theta - I_y \dot{\psi} \sin^2 \varphi \cos \theta \sin \theta - I_z \dot{\psi} \cos^2 \varphi \cos \theta \sin \theta \]
\[ + I_x \dot{\psi} \cos \theta \sin \theta \]

### 3.5.1 Complete quadrotor simulation model

From equations (3.10), (3.42), (3.14), (3.48) the complete dynamic model of the quadrotor can be written as follows:

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} =
\begin{bmatrix}
\cos \psi & \sin \psi & 0 \\
-\sin \psi \cos \theta & \cos \psi \cos \theta & \sin \theta \\
-\sin \psi \sin \theta & \cos \psi \sin \theta & \cos \theta
\end{bmatrix}
\begin{bmatrix}
c_\theta c_\psi \\ s_\theta s_\psi + c_\theta c_\psi \\ c_\theta s_\psi - s_\theta c_\psi
\end{bmatrix}
\begin{bmatrix}
u \\ v \\ w
\end{bmatrix}
\]

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} = \frac{1}{m}
\begin{bmatrix}
\cos \psi & \sin \psi & 0 \\
-\sin \psi \cos \theta & \cos \psi \cos \theta & \sin \theta \\
-\sin \psi \sin \theta & \cos \psi \sin \theta & \cos \theta
\end{bmatrix}
\begin{bmatrix}
c_\theta c_\psi \\ s_\theta s_\psi + c_\theta c_\psi \\ c_\theta s_\psi - s_\theta c_\psi
\end{bmatrix}
\begin{bmatrix}
u \\ v \\ w
\end{bmatrix}
\]

\[
\begin{bmatrix}
\dot{\varphi} \\
\dot{\theta} \\
\dot{\psi}
\end{bmatrix} =
\begin{bmatrix}
1 & s_\varphi \tan \theta & c_\varphi \tan \theta \\
0 & c_\varphi & -s_\varphi \\
0 & s_\varphi \sec \theta & c_\varphi \sec \theta
\end{bmatrix}
\begin{bmatrix}
p \\ q \\ r
\end{bmatrix}
\]

\[
\begin{bmatrix}
I_x \ddot{\varphi} \\
I_y \ddot{\theta} \\
I_z \ddot{\psi}
\end{bmatrix} =
\begin{bmatrix}
(I_y - I_z) q r \\
(I_x - I_y) p r \\
(I_x - I_y) p q
\end{bmatrix}
+ \begin{bmatrix}
\frac{1}{4} \sum_{i=1}^{4} \sin \alpha_i T_i + J_r q \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{x_i} \\
-l \sum_{i=1}^{4} \cos \alpha_i T_i - J_r p \sum_{i=1}^{4} S_{p_i} \Omega_i + \sum_{i=1}^{4} S_{p_i} B_{y_i} \\
\frac{1}{4} \sum_{i=1}^{4} S_{p_i} Q_i + l \sum_{i=1}^{4} \sin \alpha_i H_{x_i} - l \sum_{i=1}^{4} \cos \alpha_i H_{y_i}
\end{bmatrix}
\]

where sec* denotes \( \frac{1}{\cos*} \).

### 3.5.2 Simplified quadrotor simulation model

The model of the quadcopter in this thesis assumes the following characteristics:
Assumption 3.1. Assume that:

- The structure of the quadcopter and propellers are rigid and perfectly symmetrical.
- The Center of Gravity (CoG) of the quadcopter coincides with the origin of the body fixed frame.
- The thrust and drag are supposed to be proportional to the square of propeller’s speed.
- The propellers are considered to be rigid and therefore blade flapping is negligible.
- The Earth is flat and non-rotating leads to the difference of gravity by altitude or the spin of the earth is negligible.
- Surrounding fluid velocities (wind) are negligible.
- Ground effect is negligible.
- The quadrotor is hovering over a point or flying with moderate speeds (speeds do not exceed $5 \text{ m/s}$).

Under the above assumptions, we get

$$\dot{\phi} \approx p$$
$$\dot{\theta} \approx q$$
$$\dot{\psi} \approx r$$

(3.52)

Therefore, the differential system equations describing the movement of quadcopter without disturbances is obtained from (3.51a - 3.51d) as follows:

$$\ddot{x} = \left( \cos \varphi \sin \theta \cos \psi + \sin \varphi \sin \psi \right) \frac{U_1}{m}$$
(3.53a)

$$\ddot{y} = \left( \cos \varphi \sin \theta \sin \psi - \sin \varphi \cos \psi \right) \frac{U_1}{m}$$
(3.53b)

$$\ddot{z} = \left( \cos \varphi \cos \theta \right) \frac{U_1}{m} - g$$
(3.53c)

$$\ddot{\phi} = \frac{I_y - I_z}{I_x} \dot{\theta} \dot{\psi} - \frac{J_r}{I_x} \Omega_r \dot{\theta} + \frac{1}{I_x} U_2$$
(3.53d)

$$\ddot{\theta} = \frac{I_z - I_x}{I_y} \dot{\varphi} \dot{\psi} + \frac{J_r}{I_y} \Omega_r \dot{\varphi} + \frac{1}{I_y} U_3$$
(3.53e)

$$\ddot{\psi} = \frac{I_x - I_y}{I_z} \dot{\varphi} \dot{\theta} + \frac{1}{I_z} U_4$$
(3.53f)

3.6 Disturbance and parameters variations and their effect to quadcopters

Suppose that $d_x$, $d_y$, and $d_z$ are the three disturbance forces acting on the quadrotor in the direction $x$, $y$, and $z$ respectively. And there are also three disturbances moments $d_\varphi$, $d_\theta$, and $d_\psi$ acting on the quadcopter.
3.7 Conclusion

The differential system equations describing the movement of quadcopter with disturbances can be rewritten from (3.53a - 3.53f) as follows:

\[
\begin{align*}
\ddot{x} &= \left(\cos \varphi \sin \theta \cos \psi + \sin \varphi \sin \psi\right) \frac{U_1}{m} + \frac{d_x}{m} \\
\ddot{y} &= \left(\cos \varphi \sin \theta \sin \psi - \sin \varphi \cos \psi\right) \frac{U_1}{m} + \frac{d_y}{m} \\
\ddot{z} &= \left(\cos \varphi \cos \theta\right) \frac{U_1}{m} - g + \frac{d_z}{m} \\
\ddot{\varphi} &= \frac{I_y - I_z}{I_x} \dot{\theta} \dot{\psi} - \frac{J_r}{I_x} \Omega_r \dot{\theta} + \frac{1}{I_x} U_2 + \frac{d_\varphi}{I_x} \\
\ddot{\theta} &= \frac{I_z - I_x}{I_y} \dot{\varphi} \dot{\psi} + \frac{J_r}{I_y} \Omega_r \dot{\varphi} + \frac{1}{I_y} U_3 + \frac{d_\theta}{I_y} \\
\ddot{\psi} &= \frac{I_x - I_y}{I_z} \dot{\varphi} \dot{\theta} + \frac{1}{I_z} U_4 + \frac{d_\psi}{I_z}
\end{align*}
\]

During operation, some dynamic parameters of quadcopter may change. For example, the mass of quadcopter changes in agricultural applications when quadcopters are used for spraying pesticides or for irrigation of crops. As the mass changes, the moments of inertia of the quadcopter also change. Therefore, the control laws for the quadcopter need to take into account the dynamics of the varying parameters for better stabilization. In the context of this thesis, the robust Linear Parameter Varying (LPV) control laws and LPV Unknown Input Observer (UIO) will be developed for controlling and stabilizing the quadcopter.

3.7 Conclusion

In this chapter, dynamic modeling of quadrotor has been described. First, six Degrees of Freedom (DOF) rigid-body model was developed using Euler-Lagrange formalism. Next, the main acting forces and moments were included in the absence of wind. Finally, some simplifications have been considered in order to elaborate relatively simple control laws for a purpose of implementation by adopting the hierarchical control architecture.
This chapter is devoted to the Coverage Path Planning (CPP) problem for quadrotor applications in Precision Agriculture (PA). First, the basic concepts of CPP for UAV will be covered in section 4.1. Then, section 4.2 will outline the CPP problems that will be studied in the content of this thesis. There are two CPP problems in this thesis: (i) CPP for detecting the infected areas of an agricultural area, and (ii) CPP for pesticide spraying the whole infected areas that have been detected in the first CPP problem. The next two sections, 4.3 and 4.4, will study in detail the two problems of CPP prementioned above. The final section, 4.5, will be devoted to conclusions and some comments on the obtained simulation results.

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## Chapter 4. Robust Path Planning

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4.1 Preliminary concepts

4.1.1 Path generation

The path-planning problem has been intensively studied for decades in robotics. In the beginning, path planners solved the problem by a deterministic search of a discrete workspace. Then, for applying the differential constraints to the path-planning problems, the randomization techniques were studied to sample the configuration space. There are a lot of research literature on path-planning methods. One of the most significant works is the textbook of LaValle [121]. In the comprehensive surveys [130] and [84], the authors compare some algorithms on a rigorous basis such as degree of soundness, completeness, optimality, and precision.

In this subsection, only basic information of well-known basic path-planning strategies such as Graph-based and Deterministic graph search methods with some illustrations are quickly reviewed.

4.1.1.1 Graph-based methods

4.1.1.2 Dijkstra Algorithm

Dijkstra’s algorithm is an algorithm which is proposed by computer scientist Edsger W. Dijkstra in [55]. This algorithm finds the shortest paths between nodes in a graph, which may represent, for example, road networks. Its main feature is that the starting point is as the center to be extended to the end point. Each edge of the graph is formed to an ordered element pair by the two vertices. Each edge has its own value which is described by a weight function. Dijkstra’s algorithm is working in two vertex sets named $A$ and $B$. At the beginning, the set $A$ is set to empty. When a vertex in $B$ is moved to $A$, the selected vertex ensures the sum of all the edge weight from the starting point to the point is minimized. The efficiency of this algorithm is not high because it has to traverse numbers of nodes.

4.1.1.3 A* Algorithm

A* algorithm [172] was first proposed in 1968. The A* algorithm is developed on the basis of the Dijkstra algorithm. A* algorithm starts from a specific node then it updates the weighted value of the current child nodes. The child node with the smallest weighted value is used to update the current node until all nodes are traversed. The main feature of A* algorithm is that it establishes the evaluation function $f(n) = g(n) + h(n)$, where $g(n)$ is the actual cost from the initial node to the node $n$, and $h(n)$ is the estimated cost of the optimal path from node $n$ to the target node in the state space.

In most cases, the value of $h(n)$ is the Euclidean distance between the two nodes. For the case that $g(n)$ is constant, $f(n)$ is only affected by the value of the function $h(n)$. When the node is close to the target node, the value of function $h(n)$ is small leads to the value of $f(n)$ is also small. Consequently, the search for the shortest path always proceeds in the direction of the target point. The A* algorithm is more efficient than the Dijkstra algorithm as it performs informed rather than uninformed search. In addition, A* considers additional information about the minimal distance to the target (the distance function), consequently the A* algorithm expands more promising vertices than Dijkstra.
4.1.1.4 D* Algorithm

The A* algorithm is mainly applied for global search in the static environment which means that the environment does not encompass any moving obstacles. However, in practical applications, the working environment for robots always contains dynamic obstacles. To overcome this inconvenient, the D* algorithm \cite{210} was introduced in 1994. The D* algorithm is mainly used for robots to explore the path. This algorithm considers the working space as a series of states which represents the direction of the robot’s position. Another researches on D* algorithm can be found in \cite{74,108,115}.

4.1.2 Deterministic graph search

4.1.2.1 PRM (Probabilistic RoadMap)

The PRM planner is a very well-known sampling-based path planning strategies. In \cite{112}, an undirected graph $G_p$ (called roadmap) is constructed by randomly sampling the space. For each vertex in $G_p$, connections to some $k$ nearest neighboring vertices are considered. If the link between two vertices is in $D_{free}$ (the space is not occupied or obstacle-free), the corresponding edge is added to the roadmap. As more vertices and more edges are added, the roadmap data structure approximates the work-space more accurately. Both initial and goal configurations are connected to the roadmap. In \cite{111}, authors discussed the theoretical properties of the PRM algorithm. This algorithm tries to connect two nodes $p_{ini}$ and $p_{goal}$ using a graph-search method like Dijkstra’s algorithm. If there exist difficulties during the query phase, the PRM can turn back to the construction phase to adapt the size of the roadmap. A graphical representation of a roadmap is shown in Figure 4.1.

If the environment is static, the same roadmap can be reused for further or for multiple queries at the same time. This feature gives PRM the ability to be suitable for trajectory planning of multi-agent systems. However, the convergence rate is slow, and the produced paths are not optimal because the produced paths are generated based on the random points, consequently, the produced paths are only optimal with respect to the points that have been
generated. Furthermore, PRM has particular difficulty with solutions that pass through narrow passages where the performance of PRM planners can degrade as it may be less suitable for problems with significant dynamic constraints.

To overcome the shortcomings of PRM, several extension have been studied such as Lazy PRM in [27] or Medial Axis Probabilistic Roadmap planner (MAPRM) [97] [157] [237]. A version of PRM for dynamic environments is proposed in [33]. Some other PRM-based planners are in [208] [162].

### 4.1.2.2 Rapidly-exploring Random Tree (RRT)

Besides PRM another really good sampling-based planner is RRT. RRT planner can quickly find a feasible path from $p_{ini}$ to $p_{goal}$. The first publication on RRT is described in [123], and followed by a more detailed report [122]. In these two papers, the vehicle is considered holonomic, neither dynamics nor kinematic constraints are considered. In [63], the author extended the RRT to dynamic systems. Then in [65], the same author gives more extensive description to the RRT planner and a tree $T$ is created in $D_{free}$. In this paper, the author also proposed that collision-free configurations that can be reached are represented by the nodes and feasible collision-free paths between nodes are represented by edges. The root node of the tree is the initial configuration $p_{ini}$. The tree is growing and exploring $D_{free}$ until a path is found, means that there exists a path between $p_{ini}$ and $p_{goal}$ as in Figure 4.2.

![Rapidly-exploring random tree - Connection distance = 0.1](image)

![Rapidly-exploring random tree - Connection distance = 0.05](image)

**Figure 4.2:** Path planning by **RRT**

### 4.1.2.3 RRT-connect

RRT-connect is a variant of RRT. It is designed specifically for path planning problems that involve no differential constraints. The RRT-Connect planner is based on two ideas: (i) the Connect heuristic that attempts to move over a longer distance, and (ii) the growth of RRTs from both $p_{ini}$ and $p_{goal}$. With these extensions, the search tree converges rapidly to a solution. Nevertheless, this variant of RRT also has a limitation with narrow passages and
high constrained workspaces [103]. Another approach [124] proposed a Selective Retraction-based RRT Planner (SR−RRT) that efficiently handles a wide variety of environments that have different characteristics.

### 4.2 Coverage path planning problems formulation

Suppose we have a rectangular agricultural area as shown in Figure 4.3. Note that this is not the restriction because if the agricultural area is not rectangular (polygon ABCDEFG in Figure 4.4), we can add some no-fly-zone to the original agricultural area to get the new rectangular agricultural area (polygon MNPQ). The simplest way to get a rectangular agricultural area is to get the smallest rectangle containing the entire original agricultural area as in Figure 4.4.

The agricultural area (Figure 4.3) contains

- Obstacles, which are the yellow polygons. These obstacles can be convex or concave polygons, and they are the non-fly-zone,
- The white areas are areas where the plants are free of pests,
4.2. Coverage path planning problems formulation

- The red dots are areas where crops are infected,
- The coordinates of the obstacles are assumed known prior, while the coordinates of the infected crops (red dots) are not known in prior.

![Figure 4.4: Coverage path planning problem formulation](image)

**Augmentation of obstacle sizes**

In the process of performing its tasks, the UAV has to avoid the obstacles. Therefore, the distance from the center of the UAV to any point in the obstacles should be greater or equal to the radius $r$ of the smallest circle which covers the UAV (Figure 4.5a). For simplicity, consider the UAV as a point, it is necessary to augment the size of the obstacles by a radius depending on the size of the UAV. At each border point of the obstacle, the operator draws a circle with radius $r$ and creates the new obstacle inside the red curve (in Figure 4.5a). However, the augmented obstacle now is no longer a polygon.

![Figure 4.5: Augmentation of the size of obstacles](image)

(a) Augmented obstacle by using circle  
(b) Augmented obstacle by using Minkowski sum
In this study, we use another solution to augment the size of obstacle such that the augmented obstacle is a polygon. Suppose that the shape of the UAV is a square that its edge is greater than diameter of the UAV (Figure 4.5b). Let us denote the set of vertices of this square by $A$, and the set of vertices of the obstacles by $B$. The augmented obstacle is generated is the Minkowski sum \[ A \oplus B = \{ x + y | x \in A, y \in B \} \]

It is easy to prove that in the worst case scenario, when the center of the UAV is on the edge of augmented obstacle, the distance from the center of the UAV to the real obstacle (green polygon in Fig 4.5b) is always greater than the radius of the UAV and the UAV will not collide with the obstacle.

**Tasks to be solved**

Our main tasks are:

1. **Infected areas detection**: We have to detect the coordinates of all the infected areas of crops by using UAV which is equipped with a special camera. It means that the coordinates of all the red dots in Figure 4.3 should be determined. Several requirements are needed to be satisfied while performing the infected areas detection task
   - UAV has to avoid the obstacles.
   - Maximize the infected areas that can be detected.
   - Minimize the path length for the UAV.

2. **Pesticide spraying**: With the information about the coordinates of all the infected areas (coordinates of all the red dots in Figure 4.3), we have to spray the pesticide to all the infected areas of crops by using UAV which is equipped with pesticide tank. Several requirements are needed to be satisfied while performing the infected areas detection task
   - UAV has to avoid the obstacles.
   - Pesticide should be sprayed to all the infected areas that have been detected from the Infected areas detection task
   - Minimize the path length for the UAV.

### 4.3 Infected areas detection

#### 4.3.1 Problem formulation

As we have discussed in Section 4.2, the main task of this section is to determine the coordinates of all the infected areas. To do this, the entire agricultural area must be taken by specialized cameras. The gathered images will be analyzed using specialized image processing algorithms. From there, the positions of an infected crop can be identified. Thus, the problem of detecting all the crops affected by pests will be converted into the problem CPP of all the agricultural areas.
Herein, we present a new approach for maximizing the coverage path planning while minimizing the path length of an aerial robot in agriculture environment with concave obstacles. For resolving this problem, we propose a new Cellular Decomposition (CD) which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a decrease of the number of cells after decomposition. The results show that this new CD works well even with several concave obstacles inside the environment. Furthermore, for path planning, the cells are divided again into two classes, leading to have a cell set better suited for use of the TSP to get complete coverage. Genetic Algorithm (GA) and Travelling Salesman Problem (TSP) algorithms are applied to obtain the shortest path. Then, an approach is also proposed to maximize the scanned area on the working area with obstacles.

**UAV platform**

This section considers a quad-rotor equipped with a special spectral camera mounted on a gimbal stabilizer, which compensates for small rotation displacements that may be experienced by the UAV during navigation. The objective of the mission is to capture images of the whole area of plants by a dedicated spectral camera. Based on spectrum study of images that have been taken, one can have the information about the health and pest of the plant.

We assume that images are taken by special spectral camera which has the following parameters:

- Image frame is rectangle with the length and width are respectively $L$ and $H$ as depicted in Figure 4.6.
- Images have to be taken such that they have the same direction and the overlap regions on the horizontal and vertical sides as $dL$ and $dH$ (in Figure 4.7).

![Figure 4.6: UAV with frame picture capture](image1)

![Figure 4.7: Picture frames](image2)
4.3.2 Proposed algorithm for infected areas detection

The contribution of this section focuses on maximizing the coverage path planning and minimizing the path length of an aerial robot in agriculture environment with concave obstacles. The algorithm is depicted in Figure 4.8. It is a combination of distance minimization and profit maximization. For accomplishing this problem, one has to resolve three main tasks.

The first task is dedicated for CD (Figure 4.8). A new CD is based on a generalization of the Boustrophedon variant [45], using Morse functions [225], with an extension of the representation of the critical points. The feature of this extension is that the number of cells after decomposition is decreased compared to the decomposition methods in [45], [225]. With this new proposed approach, the environment can be divided into a number of separating obstacles and obstacle-free regions. In each obstacle-free region which can be called obstacle-free cell, the aerial robot can make back and forth motion to cover the whole working area.

Based on the cells that have been decomposed by CD, the second task is aiming to generate way-points in each cell (WG in Figure 4.8) and maximize the percentage of coverage (OSA in Figure 4.8). The trade-off condition between percentage of coverage and number of way-points is the condition for ending the algorithm.

Finally, in the third task, once the cells have been created by CD, the way-points have been created by WG and OSA, the cells are divided again into two classes, leading to have a cell set better suited for using the TSP algorithm to get complete coverage. GA and TSP algorithms with some modifications are applied to obtain the shortest path for the UAV to make complete coverage.
4.3. Infected areas detection

4.3.2.1 Cellular Decomposition (CD)

Several CD methods have been studied as trapezoidal decomposition technique [120], boustrophedon decomposition [45], and Morse-based CD [225].

In the trapezoidal decomposition technique [120], the free spaces are divided into trapezoidal cells. There are two parallel sides on each cell, and each cell can be covered by simple back and forth motion parallel to either side. Therefore, the whole working area can be totally scanned by visiting each cell in the adjacency graph. A vertical line is swept from left to right through the working area of the robot. Each time the line encounters a vertex of a polygon, one can say that an event occurs. Three types of events are defined: IN, OUT, and MIDDLE. In an IN event, the current cell is closed and two new cells are opened. When an OUT event occurs, the current two cells are closed and a new cell is created. Finally, MIDDLE event is the event that a current cell is closed and a new single cell is initiated. Consequently, by using these three events, the environment can be totally divided into separated trapezoidal cells.

A drawback of the trapezoidal decomposition is that it generates many cells that, intuitively, can be merged together to form bigger cells. This is clearly an inconvenient, as the more cells are present, the longer the final coverage path is. This happens because the trapezoidal decomposition creates only convex cells. However, non-convex cells can also be completely covered by simple motions. To overcome this limitation, the boustrophedon CD was proposed. The boustrophedon decomposition is similar to the trapezoidal decomposition introduced above, but it only considers vertices where a vertical segment can be extended both above and below the vertex. The vertices where this occurs are called critical points.

The boustrophedon decomposition [45] addresses the issue of redundant movements by merging together cells between successive IN and OUT movements. The major difference is in the case of a MIDDLE event, where no new cell is formed, but the current cell is updated in width. So cells are only created on change of connectivity, as a result the number of cells are less than in the case of trapezoidal decomposition. The point which changes the connectivity of the cell is termed as a critical point. In the implementation of this algorithm, the MIDDLE event is replaced by two new events called – FLOOR and CEILING. The FLOOR event corresponds to vertices on top of obstacles, while CEILING event corresponds to vertices that are at the bottom of obstacles. Both an IN event as well as an OUT event are associated with FLOOR and CEILING pointers. So for a given cell, CEILING and FLOOR pointers points to the top and bottom of a cell.

In [225], Acar et al generalized the boustrophedon decomposition by proposing a CD approach based on critical points of Morse functions. In this paper, the authors show that the boustrophedon decomposition is a particular case of Morse decomposition. With respect to the original boustrophedon decomposition, the Morse-based decomposition has the advantage of handling also non-polygonal obstacles. By choosing different Morse functions, different cell shapes are obtained, e.g. circular or spiked cells. Theoretically, Morse-decomposition can be applied to any n-dimensional space. Moreover, they presented a method to perform coverage of planar spaces by detecting the critical points using sensory range information, and a motion-template-based algorithm that ensures to encounter all the critical points in the target area. Therefore, this method allows complete coverage on line.
Chapter 4. Robust Path Planning

A new approach for CD will be proposed here. Based on the Morse method, critical points can be determined. However, Morse method does not categorize the type of critical points. In this approach critical points are categorized into four groups as follows (Figure 4.9b):

- Critical point IN type 1 (red circle): the connectivity of a slice is increased by one and the obstacle is on the right.
- Critical point IN type 2 (blue circle): the connectivity of a slice is increased by one and the obstacle is on the left.
- Critical point OUT type 1 (red square): the connectivity of a slice is decreased by one and the obstacle is on the left.
- Critical point OUT type 2 (blue square): connectivity of a slice is decreased by one and the obstacle is on the right.

The algorithm for decomposing the cluttered environment to cells is shown as follows:

- Step 1: Use a vertical line and sweep it from the left to the right of the environment, and find all the critical points.
- Step 2:
  - At each critical point IN type 1, draw a horizontal line to the left till when that line touches the obstacle or the border of the area.
  - At each critical point OUT type 1, draw a horizontal line to the right till that line touches the obstacle or the border of the area.

The results of the original boustrophedon method and the CD of this approach are shown in Figure 4.9b and 4.9a.

Remark 4.1. In Figure 4.9b and 4.9a, the vertical line sweep from the left to the right. In principle, however, the vertical line can be swept from the right to the left, from the bottom to the top, from the top to the bottom, or in any direction.

Simulation results analysis

This approach has been run and verified in Matlab. From Figure 4.9b and 4.9a, one can see that with our approach, the area has been splitted into two cells compared with four cells of the Boustrophedon decomposition method. Area with complicated forms (convex, non-convex, polygon, and arbitrary shape) (Figure 4.10) of obstacles has been divided to
4.3. Infected areas detection

only 6 cells (Figure 4.17) by using the new proposed approach, compared with more than 20 cells if using Boustrophedon method. In Figure 4.11 shows the critical points.
Remark 4.2. In this simulation, the vertical line is swept from the top to the bottom to get fewer cell compared to the case that the vertical line is swept from the left to the right.

![Cells after decomposition](image)

**Figure 4.12: Cells after decomposition**

4.3.2.2 Way-points generation (WG)

As described in section 4.3.1, picture frames which are taken by the camera mounted on the aerial robot are rectangular. Consequently, for gathering the whole area of the environment, frames need to be arranged as in Figure 4.7. Centers of these rectangles are the positions of the UAV in which the pictures will be taken. We can see that the set of all these points is the set of way-points that the UAV has to visit.

Remark 4.3. In rectangular picture frames, as shown in Figure 4.13, there are several rectangles that have a center (red star in Figure 4.14) belonging to the obstacles. These are the locations that UAV can not reach since they are located in the no-fly-zone regions.

Remark 4.4. In many cases, the center of the rectangular frames on the right most and bottom may not be within the area of the agricultural area we are working with. Therefore, the algorithm needs to recalculate the positions of the rectangles so that they are within the agricultural land under consideration.

Way-points are generated as follows:

- The first rectangle on the top left corner has the center with coordinate \((X_s, Y_s)\).
- Fill the whole working area with rectangles (Figure 4.13) from the left to the right and from the top to bottom such that two neighbor rectangles on horizontal direction have an overlapped rectangle area with dimension \(dH \times L\), and two neighbor rectangles on vertical direction have an overlapped rectangle area with dimension \(H \times dL\) (Figure 4.7).
4.3. Infected areas detection

- Find coordinates of the set $X$ that consists of all the centers of rectangles which are not located in the obstacle (Figure 4.15).
• From the coordinates of the picture frames in each cell, we have to generate the boustrophedon path as in Figure 4.16. In Figure 4.17 shows the boustrophedon trajectory in each cell and the picture frame in cell number 4.

Figure 4.15: Picture frames that centers are not in obstacles

Figure 4.16: Boustrophedon path in each cell
4.3. Infected areas detection

4.3.2.3 Optimization of the percentage of coverage (OSA)

Optimization process is processed as follows:

- Calculate the non-obstacle area of all rectangles that have been created with center in $X$.
- Find the percentage of coverage and number of images needed for the coverage.
- By varying the coordinate of the first image, means that by varying $(X_s, Y_s)$ such that $(X_s, Y_s) \in \left[1...\frac{H}{2};1...\frac{L}{L}\right]$, one can have the maximal coverage percent or minimal number or images needed to be taken.

Simulation results analysis

Simulations in this section have the following parameters:

- Image dimension : $1200 \times 700$
- Picture frame dimension
  - $H = 40; \ dH = 2$
  - $L = 80; \ dL = 2$
- trade-off function: $coverage\_percentage \times (1 - \alpha) - no\_way\_point \times \alpha$ where $\alpha = 0.2$
Table 4.1: Some results for simulations in Matlab

<table>
<thead>
<tr>
<th>Xs</th>
<th>Ys</th>
<th>Number of way-points</th>
<th>% coverage</th>
<th>Trade-off function</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>40</td>
<td>230</td>
<td>95.0196</td>
<td>30.0085</td>
</tr>
<tr>
<td>20</td>
<td>38</td>
<td>229</td>
<td>94.6407</td>
<td>29.8860</td>
</tr>
<tr>
<td>19</td>
<td>39</td>
<td>228</td>
<td>94.3653</td>
<td>29.8922</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>275</td>
<td>96.3794</td>
<td>22.1035</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>266</td>
<td>96.4520</td>
<td>23.9616</td>
</tr>
<tr>
<td>3</td>
<td>13</td>
<td>266</td>
<td>96.3549</td>
<td>23.8839</td>
</tr>
</tbody>
</table>

Simulations in this section have the following parameters:

- Image dimension: $1200 \times 700$
- Picture frame dimension
  - $H = 20; \ dH = 2$
  - $L = 40; \ dL = 2$
- trade-off function: $\text{coverage} \_\text{percentage} \times (1 - \alpha) - \text{no} \_\text{way} \_\text{point} \times \alpha$ where $\alpha = 0.2$

Table 4.2: Some results for simulations in Matlab

<table>
<thead>
<tr>
<th>Xs</th>
<th>Ys</th>
<th>Number of way-points</th>
<th>% coverage</th>
<th>Trade-off function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1044</td>
<td>97.5</td>
<td>-130.8</td>
</tr>
<tr>
<td>1</td>
<td>7</td>
<td>1048</td>
<td>97.8</td>
<td>-131.4</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>1030</td>
<td>97.9</td>
<td>-127.7</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>1026</td>
<td>97.5</td>
<td>-127.2</td>
</tr>
<tr>
<td>10</td>
<td>14</td>
<td>1031</td>
<td>97.9</td>
<td>-127.9</td>
</tr>
<tr>
<td>9</td>
<td>14</td>
<td>1029</td>
<td>97.8</td>
<td>-127.6</td>
</tr>
</tbody>
</table>

The simulation results given in table 4.1 show that, in the case when the dimension of images is large ($H = 40, dH = 2; L = 80, dL = 2$) the number of way-points affects the percentage of coverage. However, with the same trade-off function, when the dimension of images is small ($H = 20, dH = 2; L = 40, dL = 2$), the percentage of coverage seems not to be affected by the number of way-points.

4.3.2.4 Optimized path planning generation

Theoretically, it is possible to find the shortest traveling distance for all the way-points generated in the previous section. To do that, firstly, the distance between each two points needs to be calculated and the path between this two points has to avoid the obstacles. Several methods can perform that such as PRM or RRT. For instance, if there are $n$ way-points, the number of paths to be found is $\frac{n(n-1)}{2}$. After that we can use TSP for finding the shortest path between $n$ way-points. However, the calculation time can be important.

For avoiding this disadvantage, this section provides another approach. Instead of applying TSP for all the way-points, first we will split the whole area to non-obstacle separated cell
and each cell can be covered by simple back and forth motion (as has been proposed at the beginning of this section) by the UAV. Then, the TSP is applied only for finding the shortest path length for moving between cells.

In [45], the authors used the adjacency graph for finding the sequence of cells to be visited to cover the area. But this approach does not guarantee the order of visited cell gives the shortest path for changing between cells. In this section, we introduce a method for finding the cells’ sequence with the shortest path length for changing cells.

![Critical point diagram]

Figure 4.18: In/Out points in each cell

As seen in the previous section, the working area was splitted into obstacle-free cells, and the UAV can make the back and forth motion to cover cells. Consequently, for each cell, there will be two points: initial and final for the UAV coverage (Figure 4.18). For example, for cell $k$, these two points are $ka$ and $kb$. UAV can start covering the $k$th cell from point $ka$ to $kb$ or inverse from $kb$ to $ka$.

Here each cell will form two nodes of the TSP such as two nodes $cell_{1a}$ and $cell_{1b}$ for cell 1. Consequently, if the UAV is in node $cell_{1a}$, it has to go through node $cell_{1b}$ and inverse. To do this, an additional constraint has to be added to the constraints of TSP for each cell:

$$ x_{cell_{ka}cell_{kb}} + x_{cell_{kb}cell_{ka}} = 1 \quad k = 1, 2, ..., 2n $$

(4.1)

The UAV starts at initial position (START), scan the whole area and go back to the final position (STOP) for charging the battery as shown in Figure 4.19.

To ensure that there will always exist a solution for this optimization problem, the initial population for GA has the form as shown in Figure 4.21. The flip, slide and swap operations are always operated on each pair of nodes $x_a$ and $x_b$ where $x \in [1, n]$. In each iteration, the random swap position of cell $x_a$ and $x_b$ is also processed.

The flip, slide and swap operations are described in Figures 4.20b, 4.20c, 4.20a such as $i < j$.

The advantages of using proposed flip, slide, swap operations as depicted above will make the search for optimal path faster because this search is performed only on the set of paths that satisfy the given request. Furthermore, the solution is always found even though the number of cells is huge.

If proposed flip, slide, swap operations are not applied, the optimal path can only be found when the number of cell $\leq 16$, and the simulation time is always greater than 2000 seconds.
Simulation results as shown in Table 4.3 were performed on a Dell insprion 7559 with Core i7, 8Gb, Windows10, Matlab 2016b configurations specified in the table. The parameters for GA are: population\_size = 1000; number\_of\_iteration = 1e4; number\_of\_cell = 100;

<table>
<thead>
<tr>
<th>Simu</th>
<th>With proposed operations</th>
<th>Without proposed operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>732.8133 sec, solution found</td>
<td>&gt; 3000 sec, no solution</td>
</tr>
<tr>
<td>2</td>
<td>743.4828 sec, solution found</td>
<td>&gt; 3000 sec, no solution</td>
</tr>
<tr>
<td>3</td>
<td>742.2244 sec, solution found</td>
<td>&gt; 3000 sec, no solution</td>
</tr>
<tr>
<td>4</td>
<td>742.6994 sec, solution found</td>
<td>&gt; 3000 sec, no solution</td>
</tr>
</tbody>
</table>

The algorithm is shown on Algorithm 1.
4.3. Infected areas detection

(a) Swap Operation

(b) Flip Operation

(c) Slide Operation

Figure 4.20: Swap, flip, and slide operations for GA

Figure 4.22: Cellular Decomposition (CD) in the proposed approach
Algorithm 1: Genetic Algorithm and Travelling salesman problem approach

**input**: instance Π,
- population size: $4 \times \alpha$,
- number of iterations: $\delta$

**output**: Solution $X$

Generate $4 \times \alpha$ feasible solutions randomly with the form as in Figure 4.21.

Save them in the population $Pop$;

$globalMin = \infty$;

for $i \leftarrow 1$ to $\delta$ do

    // Update the best solution
    Select the best solution $minDist$ in $Pop$;
    if $minDist < globalMin$ then
        $globalMin = minDist$;

    // Mutation
    for $j \leftarrow 1$ to $\alpha$ do

        // Mutate the best to get three new routes
        Find the best solution $bs$ on 4 solutions $X_{4 \times j}$, $X_{4 \times j-1}$, $X_{4 \times j-2}$, $X_{4 \times j-3}$ of $Pop$;
        $bs_1$ is generated by flip $bs$ from random elements $I$ (node $I_a$ and node $I_b$) to $J$ (node $J_a$ and node $J_b$);
        $bs_2$ is generated by swap random element $I$ and $J$ in $bs$;
        $bs_3$ is generate by slide $bs$ from random element $I$ to $J$;
        Two gens in elements $I$ ($I \in [1, ..., n]$) of $bs_1$, $bs_2$, and $bs_3$ can be randomly swapped;

        Generate matrix $T_j$ from 4 columns matrix $bs$, $bs_1$, $bs_2$, and $bs_3$;

    // Updating
    Update $Pop = T_1 + T_2 + ... + T_\alpha$;

return the best solution $X$ in $Pop$;

---

Figure 4.23: Genetic algorithm using in the proposed approach
4.4 Pesticide spraying

The contribution of this subsection focuses on generating the best path for an UAV to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas and pests-ridden areas. The algorithm for generating this trajectory can save the working time and the amount of medicine to be distributed to the whole agriculture infected areas.

From the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. There is a trade-off between the number of classes generated and the area of all the pests-ridden areas. After that, a polygon will be found to cover each of these infected regions. However, obstacles may occupy part of the area of these polygons that have been created previously. Each polygon that is occupied in part by obstacles can be further divided into a minimum number of obstacle-free convex polygons. Then, a Boustrophedon path of optimal length will be created for each convex polygon that has been created for the UAV to follow. Finally, this subsection deals with the process of creating a minimal path for the UAV to move between all the constructed convex polygons and generate the final trajectory for the UAV which ensures that all the infected agriculture areas will be covered by the medicine.

The algorithm of the proposed method has been tested on MATLAB and can be used in precision agriculture.

4.4.1 Problem statement and decomposition

To fix ideas, suppose that the agricultural area of interest is as depicted in Figure 4.24. In this figure, there are obstacles (the yellow areas), uninfected plants (the white areas), and infected plants (the dotted red area). One can see that the infected area are close to some obstacles and an UAV which wants to move from one area to another will meet an obstacle on its path. To tackle the stated problem, we propose the algorithm illustrated in Figure 4.25. In view of this algorithm, the problem could be subdivided into four main tasks.

- The first task is MAP DIVISION (MD). From the information of the map about the coordinates of obstacles and infected areas, we divide the infected areas into several non-overlapping regions (clusters) using a clustering technique. Intuitively, the smallest shape covering each cluster is formed by the boundary of the cluster. Nevertheless, this shape does not necessarily minimize the trajectory of the UAVs. Hence we propose another approach for this cluster-covering step. In particular, we characterize the minimal convex polygon covering each cluster. Note that to ultimately determine the trajectory of the UAVs, we need to divide each covering polygon into convex regions. For this reason, the number of convex regions produced by the former approach might be larger than that of the later. In fact, which method is more efficient (i.e. producing fewer number of convex regions, smaller coverage region and shorter trajectory of the UAVs) is not known a priori; this is problem-specific. We provide an algorithm for the comparison in the simulation. However, the covering polygon of each cluster might be occupied by obstacles, which we eliminate using available coordinates data. Then, we divide each obstacles-free covering polygon into a minimum number of convex polygons.
• The second task is WAY-POINTS INFECTED AREA (WIA). We create the waypoints for each obstacle-free convex polygon (generated from the MD task) such that when the UAV follows these points, the whole area of the obstacle-free convex polygon will be covered.

• The third task is TRAJECTORY GENERATION (TG). This task aims at creating a boustrophedon trajectory for each convex polygon that has been created in MD. After that, by applying the TSP method, we can find the shortest path for the aerial robot to cover the whole polygon.

• The fourth task consists in finding the best path for the UAV to change between infected regions without colliding with obstacles.

4.4.1.1 UAV platform

This study deals with the spraying pesticide to plant by using UAV. Consequently, the UAV should be equipped with a mechanism that can spray the crop. We also assume that the distance from the UAV to the crop is \( h(m) \) and a radial area of radius \( R \) (Figure 4.26) of the crop below the UAV will be covered by the pesticide.
4.4. Pesticide spraying

4.4.2 Map division (MD)

The purpose of this section is to generate convex polygons which cover all the pest-ridden areas in the agriculture area with non-convex obstacles (Figure 4.24).

4.4.2.1 Classification of infected areas

The question now is that from the data of the coordinates of the pests, we need to group them into smaller non-intersecting areas. This task can be completed using clustering algorithms[93, 226]. Cluster analysis or clustering is a Machine Learning technique whose task is grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters). Each data point of a given set of data points can be classified into a specific cluster. Data points in the same cluster should have analogous features or properties, while data points in different clusters should have highly dissimilar features or properties. This technique is widely applied in exploratory data mining, pattern recognition, image analysis, information retrieval, bioinformatics, data compression, and computer graphics.

In this study, we adopt the K-means algorithm [102], the output of which is illustrated in Figure 4.27 where distinct clusters are represented by different colors.
Chapter 4. Robust Path Planning

4.4.2 Calculation of polygons for covering all the infected areas

The aim of this task is to generate a polygon that contains all the infected points of each generated cluster. We propose two approaches: (i) find the minimal convex polygon which covers all the infected points in each cluster, and (ii) find the boundary polygon which covers all the infected points in each cluster. As mentioned earlier, an algorithm to compare the efficiency of the two methods will be presented in Section 4.4.3.4.

4.4.2.3 Minimal Convex Partitions

As shown in Figure 4.28, the polygon covering all infected points may occupy part of the obstacle. Therefore, a new obstacle-free polygon needs to be generated as shown in Figure 4.29.

Figure 4.27: Division infected areas to several smaller regions
4.4. Pesticide spraying

A convex partition by segments of a polygon is a decomposition into convex polygons obtained by introducing arbitrary segments \[89, 75, 7, 6\]. By applying Greene’s dynamic programming algorithm \[89\], the non-convex polygon can be divided into a minimum number of convex polygons (Figure 4.29).

The algorithm that describes the process of dividing an infected area into obstacle-free convex polygons is shown in Figure 4.30.

4.4.3 Trajectory generation (TG)

The task of this section is to create a trajectory for the UAV to cover the entire infected area in a convex polygon. There exists two common trajectories for covering a convex polygon, the first is the Boustrophedon trajectory, and the second is spiral. In this thesis, we use the boustrophedon.
4.4.3.1 Waypoints generation for convex polygon

Consider the convex polygon $ABCDEFG$ with two parallel sides $AB$ and $DE$ separated by a distance of $2R$ as shown (in Figure 4.31). Draw a parallel line at distance $R$ to the
edge \( AB \). This line intersects the sides of the convex polygon \( ABCDEFG \) at \( M \) and \( N \). Form the rectangle \( X_1X_2X_3X_4 \) with two edges \( X_1X_2 \) and \( X_3X_4 \) parallel to edge \( AB \) and \( X_1X_2 = X_3X_4 = MN \). When the \( \text{UAV} \) moves from \( M \) to \( N \), overlapping region between the convex polygon \( ABCDEFG \) and the rectangle \( X_1X_2X_3X_4 \) will be covered. It remains to find the path for the \( \text{UAV} \) in the uncovered regions of the \( ABCDEFG \) polygon. In Figure 4.31, these regions are made up of the triangle \( NTC \) and the quadrangle \( MEGS \). Consider first the triangle \( NTC \) to the right of \( X_1X_2 \). Observe that the furthest vertex of this triangle to point \( N \) is less than \( R \). Consequently, when the \( \text{UAV} \) is at \( N \), it will cover the area of this triangle. For the quadrangle \( MFGS \) to the left of \( X_1X_2 \), notice that its furthest vertex is \( G \). Let \( P \) be a point on the segment \( GM \) at distance \( R \) from \( G \). Since \( ABCDEFG \) is a convex polygon, the point \( P \) and the segment \( PM \) belong to the polygon \( ABCDEFG \). When the \( \text{UAV} \) moves from \( P \) to \( M \), the whole area of \( MFGS \) can be covered. Thus, \( PMN \) (the red lines in Figure 4.32) is the shortest path the \( \text{UAV} \) must follow to cover the entire area of polygon \( ABCDEFG \).

As calculated above, a moving trajectory can be calculated for convex polygons with two parallel sides of a distance \( 2R \) in between.

![Diagram](image)

(a) Split convex polygon into several trapezoids with \( \alpha \) angle  
(b) Path way with \( \alpha \) angle

Figure 4.33: Augmentation of the size of obstacles

The task now is to create the motion trajectory of the \( \text{UAV} \) over an entire convex polygon so that when the \( \text{UAV} \) moves in this orbit, its entire area can be covered. Consider a convex polygon that has been subdivided into smaller convex polygons as illustrated in Figure 4.33a by parallel lines at distance \( 2R \) from one another and at an angle \( \alpha \) to the horizontal axis.

In this fashion, the optimal trajectory for each convex polygon 1,2,3,4 can be created. Combining these trajectories, we obtain the motion trajectory between the points \( S \) and \( E \) (Figure 4.33b). When the \( \text{UAV} \) moves along this trajectory, the entire area of the polygon can be covered.

### 4.4.3.2 Trajectory generation for each convex polygon

As shown in Figure 4.33a, the generated trajectory depends on the slope of the parallel lines. Therefore, we vary the angle of these parallel lines to numerically compute the shortest path. This algorithm is shown in Figure 4.34. There is an optimal \( \alpha \) for each convex polygon.
By using the algorithm in Figure 4.34, we can create the shortest trajectory for each convex polygon region so that when the UAV follows that path, the entire area of the convex polygon will be covered (Figure 4.35).

4.4.3.3 Trajectory generation for entire agriculture area

As a result of the previous section, the Boustrophedon trajectory was generated for each convex polygon. Each orbit of these convex polygons has two points $S$ and $E$. This means that when the UAV comes from point $E$, it goes to point $S$ when moving on the Boustrophedon trajectory or vice versa from $S$ to $E$, the entire area of that convex polygon will be covered. However, how the UAV can scan the entire area of a pest, also means that the UAV must move through all the generated Boustrophedon trajectory inside generated convex polygons.

An algorithm that allows finding the shortest path for UAV has been previously developed by the author [175]. By using GA with some modification on the swap, flip and slide operations and the Traveling Salesman Problem with some additional constraints, the shortest path for changing the cells has been developed. This algorithm guarantees that the solution always exists and the time for calculation is decreasing.
4.4. Pesticide spraying

4.4.3.4 Simulation results

The covered area and length of Boustrophedon trajectory

In this simulation, we compare the covered area and the trajectory length of generated Boustrophedon trajectories when each obstacle-free cluster is generated by minimal convex polygon (Figure 4.35a) and boundary polygon (Figure 4.35b). From the results in Table 4.4, we can see that the method for generating the obstacle-free by using boundary is better than the method for generating the obstacle-free by using minimal convex polygon. The area and the trajectory length for the later method are smaller than the former.

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>Minimal convex polygon</th>
<th>Boundary polygon</th>
</tr>
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<tr>
<td></td>
<td>29860</td>
<td>8119</td>
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<td></td>
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<table>
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<tr>
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<td></td>
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</tr>
<tr>
<td></td>
<td>22397</td>
<td>6664</td>
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</tbody>
</table>

Number of classes vs covered area and length of Boustrophedon trajectory

In this simulation, we are going to compare the trajectory length when the pest-ridden areas of an agricultural area are divided into different numbers of classes. The result is shown in Figure 4.36.
From the results in Table 4.5, we can see that the number of clusters affects the area of polygon needed to be covered and generated trajectory. When the number of cluster is higher, the area of polygon needed to be covered and generated trajectory are lower. Beside that, the method for generating the obstacle-free by using boundary polygon is better than the method for generating the obstacle-free by using minimal convex polygon. However, the number of divided convex polygons with the boundary polygon is much higher than the number of divided convex polygons with the minimal convex polygon decomposition. This number affects the length of trajectory for changing between divided convex polygons.

**Figure 4.36:** Simulation result
Table 4.5: Classes number vs Trajectory path length

<table>
<thead>
<tr>
<th>No Cl.</th>
<th>Division method</th>
<th>No con. polygon</th>
<th>Area(\text{m}^2)</th>
<th>Trajectory length(\text{m})</th>
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<tr>
<td>5</td>
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<td>204158</td>
<td>59574</td>
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<td>10</td>
<td>Min. con. polygon</td>
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<td></td>
<td>26</td>
<td>221521</td>
<td>59350</td>
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<tr>
<td></td>
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<td>54729</td>
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<tr>
<td></td>
<td></td>
<td>76</td>
<td>196747</td>
<td>54123</td>
</tr>
</tbody>
</table>

4.5 Conclusion

In this chapter, we have studied two tasks for the quadrotor to be used in PA:

- Infected area detection
- Pesticide spraying all the infected areas

For the first task, we have proposed a new approach for maximizing the coverage area and minimizing the path length of an aerial robot in agriculture environment with concave obstacles. Firstly, we propose a new approach for cellular decomposition. Based on the critical points as in [45] and [225], the extension of this approach is that the critical points have been categorized to several groups, and the cells have been created from these groups. This extension leads to a decrease of the number of cells after decomposition. The results show that this new cellular decomposition works well even with several concave obstacles inside the environment.

Secondly, we have proposed a method for maximizing the percentage of coverage and we have given some comments for the trade-off between the percentage of coverage and the number of way-points for the UAV. The percentage of coverage is up to 97.9%.
Finally, by using GA with some modification on the swap, flip and slide operations and the TSP with some additional constraints, the shortest path for changing the cells has been developed. This algorithm guarantees that the solution always exists and the time for calculation is decreasing.

For the second task, we have proposed a method for generating a trajectory which allows the UAV to put the medicine to the entire pest-ridden area of an agricultural area. First, the pest-ridden areas have been divided into several smaller areas (clusters) by using clustering technique. After that, each cluster is divided again to several obstacle-free convex polygons. Then the shortest Boustrophedon trajectory is created in each obstacle-free convex polygon. Finally, the shortest trajectory for changing between obstacle-free convex polygons is generated to form the final trajectory.

Several extensions from this section are possible. One might consider the recalculating the trajectory under the windy condition of the environment or trajectory generation for a team of UAV. Field tests are also subject of future work. The continuation of this work is also to add the UAV equations of motion as constraints on the path. Then the efficiency of the algorithm will be improved to be real-time usable.
Nonlinear robust control and state estimation of UAVs

Chapter abstract

Motion control design plays a crucial role in aerial autonomous vehicles for accomplishing the predefined tasks. The UAV faces a variety of disturbances when performing outdoor missions. Especially for the duty of spraying pesticides or transporting goods, the mass of the Unmanned Aerial Vehicle (UAV) changes. It is followed by the changes in dynamic parameters such as the moments of inertia. Therefore, developing a suitable control algorithm that is robustly stable under the external disturbances and the changes of parameters is essential. This chapter is organized as follows: in Section 5.1 we take a quick look at the control system of the quadcopter. Due to the changes of the mass and moments of inertia, their values should be calculated or estimated and will be presented in section 5.2. Then, the position/altitude control of quadcopter is shown in section 5.3. In the next section 5.4 the dynamic output feedback controller will be designed for the attitude subsystem of the quadcopter. Next, the Attitude/Altitude LPV Unknown Input Observer (UIO) of mass-varying quadcopter is designed in section 5.5. The Attitude/Altitude LPV $H_\infty$ State feedback Controller and Static output feedback LPV for mass-varying controller are presented respectively in sections 5.6 and 5.7. Finally, the conclusions are given in the last section.

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## Chapter 5. Nonlinear robust control and state estimation of UAVs

### 5.4.4 Comments on the simulation results

### 5.5 Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)

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### 5.6 Attitude/Altitude LPV $H_\infty$ State feedback Controller

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### 5.7 LPV Static output feedback controller for Attitude/Altitude

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### 5.8 Conclusion

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5.1 Control system for quadcopter

For the purpose of convenience, the mathematical equations of the quadcopter model without disturbances in (3.53) can be written as follows:

\[
\begin{align*}
\ddot{x} &= (\cos \varphi \sin \theta \cos \psi + \sin \varphi \sin \psi) \frac{U_1}{m} \quad (5.1a) \\
\ddot{y} &= (\cos \varphi \sin \theta \sin \psi - \sin \varphi \cos \psi) \frac{U_1}{m} \quad (5.1b) \\
\ddot{z} &= (\cos \varphi \cos \theta) \frac{U_1}{m} - g \quad (5.1c) \\
\dot{\phi} &= \frac{I_y - I_z}{I_x} \dot{\psi} - \frac{J_r}{I_x} \Omega_r \dot{\theta} + \frac{1}{I_x} U_2 \quad (5.1d) \\
\dot{\theta} &= \frac{I_z - I_x}{I_y} \dot{\varphi} \dot{\psi} + \frac{J_r}{I_y} \Omega_r \dot{\varphi} + \frac{1}{I_y} U_3 \quad (5.1e) \\
\dot{\psi} &= \frac{I_x - I_y}{I_z} \dot{\varphi} \dot{\psi} + \frac{1}{I_z} U_4 \quad (5.1f)
\end{align*}
\]

The system can be rewritten in the state-space form

\[ \dot{X} = f(X,U) \quad (5.2) \]

where \( U \) is the input vector and \( X \) denotes the state vector chosen as follows:

\[
\begin{align*}
X &= [x \ y \ z \ \varphi \ \psi \ \dot{x} \ \dot{y} \ \dot{z} \ \dot{\varphi} \ \dot{\psi}]^T \quad (5.3a) \\
U &= [U_1 \ U_2 \ U_3 \ U_4]^T \quad (5.3b)
\end{align*}
\]

where inputs are mapped by

\[
\begin{align*}
U_1 &= k_f \left( \omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2 \right) \\
U_2 &= k_f \left( -\omega_2^2 + \omega_4^2 \right) \\
U_3 &= k_f \left( \omega_1^2 - \omega_3^2 \right) \\
U_4 &= k_z \left( -\omega_1^2 + \omega_2^2 - \omega_3^2 + \omega_4^2 \right)
\end{align*}
\]

and

\[ \Omega_r = \omega_1 - \omega_2 + \omega_3 - \omega_4 \quad (5.5) \]

where \( \omega_i \) for \( i = 1, 2, 3, 4 \) denotes the \( i \)-th rotor velocity, and \( T_i \) for \( i = 1, 2, 3, 4 \) are the thrust generated by the \( i \)-th rotor and the thrust \( T_i(t) \) is a function of the rotor speed defined by

\[
T_i(t) = k_f \omega_i^2 \quad (5.6)
\]
where $k_f$ and $k_z$ are the constant coefficients, and

$$f(X,U) = \begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z} \\
\dot{\phi} \\
\dot{\theta} \\
\dot{\psi} \\
u_x U_1 \\
u_y U_1 \\
I_y - I_z \dot{\phi} \dot{\psi} - I_x \Omega_z \dot{\theta} + \frac{1}{I_x} U_2 \\
I_x - I_z \dot{\phi} \dot{\psi} + I_y \Omega_x \dot{\phi} + \frac{1}{I_y} U_3 \\
I_x - I_z \dot{\phi} \dot{\theta} + \frac{1}{I_z} U_4
\end{bmatrix}$$ (5.7)

where

$$u_x = \cos \varphi \sin \theta \cos \psi + \sin \varphi \sin \psi$$  \hspace{0.5cm} (5.8a) \\
u_y = \cos \varphi \sin \theta \sin \psi - \sin \varphi \cos \psi$$  \hspace{0.5cm} (5.8b)

It is worthwhile to note in the latter system that the angles and their time derivatives do not depend on translation components. On the other hand, the translations depend on the angles. One can ideally imagine the overall system described by (5.7) as constituted of two subsystems, the angular rotations and the linear translations (see Figure. 5.1).

![Figure 5.1: Connection between rotational and translational subsystems of the quadcopter](image)

Therefore the control system of the quadcopter can be divided into subcontrollers such as position controller (for controlling $x$ and $y$), altitude controller (for controlling $z$), and attitude controller (for controlling three Euler angles $\phi$, $\theta$, and $\psi$) as described in Figure 5.2.
5.2 Quadrotor’s states and parameters estimation

5.2.1 State estimation overview

Thanks to the maneuverability, low cost and ability to hover in place, the quadrotors have been widely applied in applications for a variety of dangerous or complex tasks, such as inspection [166] [247], search and rescue [149], exploration [220], interaction with the environment [218] [77], transportation [135], and mapping [136]. To ensure the successful completion of the aforementioned tasks, precise control, and reliable navigation performance are essential. Therefore, the accurate knowledge of the vehicle’s physical characteristics and its states plays a really critical role.

In [236], the state variables (position, velocities, and attitude) of an autonomous quadrotor UAV were estimated by using the Kalman Filter (KF) under the condition of sufficient measurements. In [66], the quadrotor’s attitude was estimated by using two Extended Kalman Filters (EKF) along with a Direction Cosine Matrix (DCM) algorithm for a single low-cost IMU sensor. Also in this work, the authors use Extended Kalman Filter (EKF) for filtering a 3-axis gyro sensor to detect the angular rate, then Euler angles are calculated through the DCM algorithm using the filtered gyro and magnetometer sensor. Then, another EKF is used to enhance the estimation of the Euler angles. In [241], the authors use Optimal Kalman Filter (OKF) to estimate the state variables of the quadrotor under the presence of the white Gaussian process and measurement noises, which are caused by the actuator and sensor faults, respectively.

5.2.2 Quadrotor’s parameters estimation

Besides the state variables, other dynamic parameters such as mass and moments of inertia are also important and need to be determined accurately.

In [129] and [113], the authors proposed approaches based on kinematic models. They identify the spatial-temporal poses of sensors such as IMU, monocular or stereo cameras. To estimate the inertia properties, the authors combine the IMU pose sensor, and motor
speed measurements. This not only allows the estimation of relative positions of the different sensor modules and the linear and rotational IMU biases but also the position of the Center of Mass, the Moment of Inertia and the mass.

In [148], the frequency-domain approach is used for determining the Moment of Inertia of the quadrotor. This work does not use a probabilistic framework to eliminate the noise and uncertainty associated with the sensor data. This approach also limits the motions of the system to one axis at a time and unable to estimate the position of the center of mass.

### 5.2.3 Calculation/estimation of mass and moments of inertia

When the UAV sprays pesticides or delivers packages, the mass of the UAV decreases gradually or abruptly. In both cases, the total mass of the UAV is the same and is assumed to contain several smaller cylinders. In the case of gradual mass reduction, the number of cylinders is much larger than the case of a abrupt mass change.

In particular, we assume that there are $n$ cylinders $m_1, m_2, ..., m_n$ attached to the UAV as shown in Fig. 5.3. Each cylinder $m_i, i = 1, ..., n$ has the height $h_i$, radius $r$, and mass $m_i$. To simulate the process of reducing the mass of the UAV, the cylinders $m_i, i = 1, ..., m$ will be sequentially $(m_n, ..., m_1)$ detached from the UAV over time. We call $x_k$, $y_k$, and $z_k$ (Fig. 5.3) the three axes $x$, $y$, and $z$ for calculation the moments of inertia of the mass which contains $k$ cylinders from 1 to $k$, where $k = 1, ..., n$.

Due to the variation of the mass of the UAV over time, the moments of inertia will also change. Therefore, the moments of inertia of the whole system need to be recalculated at each change. Moments of inertia of mass $(m_1 + ... + m_k), k = 1, ..., n$ with respect to their $x$
and \( y \) axes \( x_k \) and \( y_k \) respectively are:
\[
J_{(m_1+...+m_k)/x_k} = J_{(m_1+...+m_k)/y_k} = \left( \sum_{i=1}^{k} m_i \right) \frac{r^2}{4} + \left( \sum_{i=1}^{k} m_i \right) \frac{h_i}{12} \left( \frac{\sum_{i=1}^{k} h_i}{4} \right)^2
\]  
(5.9)

Hence, moments of inertia of mass \( (m_1 + ... + m_k) \), \( k = 1,...,n \) with respect to the axes \( x_q \) and \( y_q \) of the quadcopter are:
\[
J_{(m_1+...+m_k)/x_q} = J_{(m_1+...+m_k)/y_q} = J_{(m_1+...+m_k)/z_q} = \left( \sum_{i=1}^{k} m_i \right) \frac{r^2}{2}
\]  
(5.10)

Moments of inertia of mass \( (m_1 + ... + m_k) \), \( k = 1,...,n \) with respect to their \( z_k \) axes and the \( z_q \) axis of the quadcopter are:
\[
J_{(m_1+...+m_k)/z_k} = J_{(m_1+...+m_k)/z_q} = \left( \sum_{i=1}^{k} m_i \right) \frac{r^2}{2}
\]  
(5.11)

Finally, moments of inertia of a system which contains the quadcopter and \( k \) cylinders \( m_1,...,m_k \) for \( k = 1,...,n \) with respect to the three axis of the quadcopter \( x_q, y_q, \) and \( z_q \) are:
\[
J_{\text{quad}(m_1+...+m_k)/x_q} = J_{\text{quad}/x_q} + J_{(m_1+...+m_k)/x_q} = J_{\text{quad}/x_q} + \sum_{i=1}^{k} m_i \left( \frac{r^2}{4} + \frac{7}{12} \left( \sum_{i=1}^{k} h_i \right)^2 \right)
\]  
(5.12)

\[
J_{\text{quad}(m_1+...+m_k)/y_q} = J_{\text{quad}/y_q} + J_{(m_1+...+m_k)/y_q} = J_{\text{quad}/y_q} + \sum_{i=1}^{k} m_i \left( \frac{r^2}{4} + \frac{7}{12} \left( \sum_{i=1}^{k} h_i \right)^2 \right)
\]  
(5.13)

\[
J_{\text{quad}(m_1+...+m_k)/z_q} = J_{\text{quad}/z_q} + J_{(m_1+...+m_k)/z_q} = J_{\text{quad}/z_q} + \sum_{i=1}^{k} m_i \left( \frac{r^2}{2} \right)
\]  
(5.14)

### 5.3 Position/Altitude control

In this section, the translational subsystem will be considered. The differential equations of dynamic translational subsystem is given by:
\[
\begin{align*}
\ddot{x} &= (\sin \psi \sin \varphi + \cos \psi \sin \theta \cos \varphi) \frac{U_1}{m} \\
\ddot{y} &= (\sin \psi \sin \theta \cos \varphi - \cos \psi \sin \varphi) \frac{U_1}{m} \\
\ddot{z} &= (\cos \theta \cos \varphi) \frac{U_1}{m} - g
\end{align*}
\]  
(5.15)
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The state vector is then defined by:

\[
X = \begin{bmatrix} x & \dot{x} & y & \dot{y} & z & \dot{z} \end{bmatrix}^T = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 \end{bmatrix}^T
\]

5.3.1 Position control

As \(U_1\) controls \(z\), we can only define desired \(\phi_{\text{ref}}\) and \(\theta_{\text{ref}}\) to be computed to achieve that \(x_c\) and \(y_c\) go to desired \(x_{\text{ref}}\) and \(y_{\text{ref}}\).

In this subsection, a simple PD controller is designed for calculating the required roll \(\phi_{\text{ref}}\) and pitch \(\theta_{\text{ref}}\).

We define the position and velocity errors \(x\) and \(y\) as:

\[
\begin{align*}
ep_x &= x_{\text{ref}} - x \\
ep_{\dot{x}} &= \dot{x}_{\text{ref}} - \dot{x} \\
ep_y &= y_{\text{ref}} - y \\
ep_{\dot{y}} &= \dot{y}_{\text{ref}} - \dot{y}
\end{align*}
\]

And we want these errors to decay exponentially to 0.

If we take the error term and make it obey a second order linear differential equation with proper coefficients, we can guarantee that the error goes exponentially to 0.

Means:

\[
\begin{align*}
\ddot{x}_{\text{ref}} - \ddot{x}_c + K_{dx} \dot{e}_{\dot{x}} + K_{px} e_{px} &= 0 \\
\ddot{y}_{\text{req}} - \ddot{y}_c + K_{dy} \dot{e}_{\dot{y}} + K_{py} e_{py} &= 0
\end{align*}
\]

where \(\ddot{x}_c\) and \(\ddot{y}_c\) are the commanded accelerations which are calculated by the controller.

Hence, the second derivative of commanded \(x_c\) and \(y_c\) are calculated as:

\[
\begin{align*}
\ddot{x}_c &= \ddot{x}_{\text{ref}} + K_{px} (x_{\text{ref}} - x) + K_{dz} (\dot{x}_{\text{ref}} - \dot{x}) \\
\ddot{y}_c &= \ddot{y}_{\text{ref}} + K_{py} (y_{\text{ref}} - y) + K_{dy} (\dot{y}_{\text{ref}} - \dot{y})
\end{align*}
\]

Suppose that the quadcopter is around the hover position, we have:

\[
\begin{align*}
U_1 &\approx mg \\
\theta &\approx 0 \\
\phi &\approx 0 \\
\psi &\approx \psi_{\text{ref}}
\end{align*}
\]

Therefore, the required \(\phi_{\text{ref}}\) and \(\theta_{\text{ref}}\) can be obtained as:

\[
\begin{align*}
\phi_{\text{ref}} &= \frac{1}{g} (\ddot{x}_c \cdot \sin \psi_{\text{ref}} - \ddot{y}_c \cdot \cos \psi_{\text{ref}}) \\
\theta_{\text{ref}} &= \frac{1}{g} (\ddot{x}_c \cdot \cos \psi_{\text{ref}} + \ddot{y}_c \cdot \cos \psi_{\text{ref}})
\end{align*}
\]

(5.17)

Coefficients of PD controller are selected to ensure stability and the responses to trajectory tracking as follows:

\[
K_{px} = 20; \quad K_{dz} = 2; \quad K_{py} = 25; \quad K_{dy} = 3
\]
5.3.2 Altitude control

In this subsection, we design an integral back-stepping controller for altitude of the quadcopter which is able to track the reference. The error of the altitude \( z \) (state \( x_5 \)), its derivative are defined as follows:

\[
\begin{align*}
  z_5 &= x_{5d} - x_5 \\
  \dot{z}_5 &= \dot{x}_{5d} - x_6 
\end{align*}
\] (5.18)

For improving the system’s robustness against modeling uncertainties and external disturbance, thus improving steady-state control accuracy, we define also the integral of state \( x_5 \) as

\[
\xi_5 = \int_0^t z_5(\tau) d\tau 
\] (5.19)

We study the stability of the altitude system via Lyapunov theory, the Lyapunov function and its derivative are:

\[
\begin{align*}
  V(x_5) &= \frac{1}{2} z_5^2 \\
  \dot{V}(x_5) &= z_5 (\dot{x}_{5d} - x_6) 
\end{align*}
\] (5.20)

We can see no direct control law in (5.20). Consequently, \( x_6 \) is defined as a virtual control. To make \( \dot{V}(x_5) \) negative semi-definite, the desired virtual control is defined as:

\[
\begin{align*}
  x_{6d} &= \dot{x}_{5d} + c_5 z_5 + \lambda_5 \xi_5 
\end{align*}
\] (5.21)

where \( c_5 \) and \( \lambda_5 \) are positive numbers.

In order to make \( x_6 \) follows the stabilizing function \( x_{6d} \), we define the error state \( z_6 \) as the deviation between \( x_{6d} \) and \( x_6 \):

\[
\begin{align*}
  z_6 &= x_{6d} - x_6 
\end{align*}
\] (5.22)

The virtual control \( x_6 \) and the derivative of \( z_6 \) are:

\[
\begin{align*}
  x_6 &= \dot{x}_{5d} + c_5 z_5 + \lambda_5 \xi_5 - z_6 \\
  \dot{z}_6 &= \dot{x}_{5d} + c_5 \dot{z}_5 + \lambda_5 \dot{\xi}_5 - \frac{\cos \varphi \cos \theta}{m} U_1 + g 
\end{align*}
\] (5.23-5.24)

The Lyapunov function is extended as

\[
V_1 = \frac{1}{2} z_5^2 + \frac{1}{2} \lambda_5 \xi_5^2 
\] (5.25)

The time derivative of the Lyapunov function \( V_1 \) is:

\[
\begin{align*}
  \dot{V}_1 &= z_5 \dot{z}_5 + \lambda_5 \xi_5 \dot{\xi}_5 \\
  &= z_5 (\dot{x}_{5d} - x_6) + \lambda_5 \xi_5 z_5 \\
  &= z_5 (z_6 - c_5 z_5 - \lambda_5 \xi_5) + \lambda_5 \xi_5 z_5 \\
  &= -c_5 z_5^2 + z_5 z_6 
\end{align*}
\] (5.26)

For making the time derivative of Lyapunov function negative, \( z_6 \) should be added to it. Define the new Lyapunov function as

\[
V_2 = \frac{1}{2} z_5^2 + \frac{1}{2} \lambda_5 \xi_5^2 + \frac{1}{2} z_6^2 
\] (5.27)
Then, the derivative of the new Lyapunov function is
\[ \dot{V}_2 = -c_5 z_5^2 + z_5 z_6 + z_6 \left( \ddot{x}_{5d} + c_5 \dot{z}_5 + \lambda_5 \dot{\xi}_5 - \frac{\cos \varphi \cos \theta}{m} U_1 + g \right) \] (5.28)

For ensuring the negativity of \( \dot{V}_2 \), we choose \( U_1 \) as
\[ U_1 = \frac{m}{\cos \varphi \cos \theta} \left( \ddot{x}_{5d} \left( 1 - c_5^2 + \lambda_5 \right) z_5 - c_5 \lambda_5 \dot{\xi}_5 + (c_5 + c_6) z_6 + g \right) \] (5.29)
where \( c_6 \) is a positive number.

Then
\[ \dot{V}_2 = -c_5 z_5^2 - c_6 z_6^2 \] (5.30)

Coefficients of the Back-stepping controller are selected as:
\[ c_5 = 0.001; \quad c_6 = 30; \quad \lambda_5 = 30 \]

5.4 LPV \( H_\infty \) Attitude control

In this section, the rotational subsystem will be considered. In this section, we assume that the quadcopter is symmetric and \( I_x = I_y \).

Therefore, the differential equations of rotational dynamic subsystem is given as:
\[
\begin{align*}
\ddot{\phi} &= \frac{I_x - I_z}{I_x} \dot{\theta} \dot{\psi} - \frac{J_x \Omega_x}{I_x} \dot{\theta} + \frac{l}{I_x} U_2 \\
\ddot{\theta} &= \frac{I_z - I_x}{I_x} \dot{\phi} \dot{\psi} + \frac{J_y \Omega_y}{I_x} \dot{\phi} + \frac{l}{I_x} U_3 \\
\ddot{\psi} &= \frac{1}{I_z} U_4
\end{align*}
\] (5.31)

5.4.1 Roll-pitch \( H_\infty \) controller

The dynamic of Roll-Pitch subsystem (5.31a - 5.31b) is rewritten in descriptor form for reducing the number of subsystems as
\[
\begin{align*}
I_x \ddot{\phi} &= (I_x - I_z) \dot{\theta} \dot{\psi} - J_y \Omega_y \dot{\theta} + l U_2 \\
I_x \ddot{\theta} &= - (I_x - I_z) \dot{\phi} \dot{\psi} + J_x \Omega_x \dot{\phi} + l U_3
\end{align*}
\] (5.32)
State vector is

\[ X_{RP}^T = \begin{bmatrix} \varphi & \theta & \dot{\varphi} & \dot{\theta} \end{bmatrix}^T \]

The roll-pitch subsystem can be written as:

\[
\begin{align*}
E_{RP} \dot{X} &= A_{RP} X + B_{RP} u \\
y &= C_{RP} X + D_{RP} u
\end{align*}
\]

where:

\[
E_{RP} = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & -I_x - I_z \dot{\psi} & I_x \\
0 & 0 & I_x & 0 \\
\end{bmatrix}
\]

\[
A_{RP} = \begin{bmatrix}
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\end{bmatrix};
B_{RP} = \begin{bmatrix}
0 & 0 \\
0 & l \\
0 & 0 \\
\end{bmatrix}
\]

\[
C_{RP} = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix};
D_{RP} = \begin{bmatrix}
0 & 0 \\
0 & 0 \\
\end{bmatrix}
\]

The parameter \( \rho_{RP} \) that is varying is:

\[
\rho_{RP} = \begin{bmatrix}
I_x & (I_x - I_z) \dot{\psi} & \Omega_r \\
\rho_{RP1} & \rho_{RP2} & \rho_{RP3} \end{bmatrix}^T
\]

Their varying ranges are in table 5.1.
Table 5.1: Parameters range for LPV $H_\infty$ Roll-Pitch and Yaw controllers

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{RP1}$</td>
<td>$I_x$</td>
<td>$[0.0075, 0.0128]$ kg.m$^2$</td>
</tr>
<tr>
<td>$\rho_{RP2}$</td>
<td>$(I_x - I_z) \psi$</td>
<td>$[-5 \times 10^{-4}, 0.0173]$ kg.m$^2$</td>
</tr>
<tr>
<td>$\rho_{RP3}$</td>
<td>$\Omega_r$</td>
<td>$[-300, 300]$ rad.s$^{-1}$</td>
</tr>
<tr>
<td>$\rho_Y$</td>
<td>$I_z$</td>
<td>$[0.0130, 0.0162]$ kg.m$^2$</td>
</tr>
</tbody>
</table>

In order to express the system in a polytopic form, matrices $A_{RP}, B_{RP}, C_{RP}, D_{RP}, E_{RP}$ can be decomposed as:

\begin{align*}
A_{RP} &= A_{RP0} + \rho_{RP1} A_{RP1} + \rho_{RP2} A_{RP2} + \rho_{RP3} A_{RP3} \\
B_{RP} &= B_{RP0} + \rho_{RP1} B_{RP1} + \rho_{RP2} B_{RP2} + \rho_{RP3} B_{RP3} \\
C_{RP} &= C_{RP0} + \rho_{RP1} C_{RP1} + \rho_{RP2} C_{RP2} + \rho_{RP3} C_{RP3} \\
D_{RP} &= D_{RP0} + \rho_{RP1} D_{RP1} + \rho_{RP2} D_{RP2} + \rho_{RP3} D_{RP3} \\
E_{RP} &= E_{RP0} + \rho_{RP1} E_{RP1} + \rho_{RP2} E_{RP2} + \rho_{RP3} E_{RP3}
\end{align*}

where:

\begin{align*}
A_0 &= \begin{bmatrix} 0_2 & I_{22} \\ 0_{22} & 0_{22} \end{bmatrix}; A_1 = A_2 = A_3 = A_4 = [0_{44}] \\
B_0 &= l \begin{bmatrix} 0_{22} \\ I_{22} \end{bmatrix}; B_1 = B_2 = B_3 = B_4 = [0_{42}] \\
C_0 &= \begin{bmatrix} I_{22} & 0_{22} \end{bmatrix}; C_1 = C_2 = C_3 = C_4 = [0_{24}] \\
D_0 &= D_1 = D_2 = D_3 = D_4 = [0_{22}] \\
E_0 &= \begin{bmatrix} I_{22} & 0_{22} \\ 0_{22} & 0_{22} \end{bmatrix}; E_1 = \begin{bmatrix} 0_{22} & 0_{22} \\ 0_{22} & I_{22} \end{bmatrix}; \\
E_2 &= \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}; E_3 = \begin{bmatrix} 0_{22} & \Omega_r \\ \Omega_r & 0_{22} \end{bmatrix}
\end{align*}

Weight functions for Roll-Pitch $H_\infty$ controller are chosen as following:

\begin{align*}
W_u1 &= \frac{s}{s+100000}; W_u2 = \frac{s}{s+100000} \\
W_P1 &= \frac{1}{s+0.1}; W_P2 = \frac{1}{s+0.1}
\end{align*}

The norm of $[LPV] H_\infty$ Roll-Pitch subsystem is $\gamma_{RP} = 0.544$

**Remark 5.1.** In this simulation, $[LPV]$ gain-scheduled $H_\infty$ controller is synthesized by using the command `hinfgs` of the robust control toolbox in Matlab. Basically, this controller is the dynamic output feedback controller. This controller minimizes the closed-loop quadratic $H_\infty$ performance from reference signal $[\varphi_{ref} \theta_{ref}]^T$ to $[z_1 \ z_2 \ z_3 \ z_4]^T$ signal.
5.4.2 Yaw $H_\infty$ controller

The dynamic of Yaw subsystem \((5.31c)\) is rewritten in descriptor form as

$$I_z \ddot{\psi} = U_4 \quad (5.35)$$

The state vector is $X_Y^T = [\psi \ \dot{\psi}]^T$ and the control input is $u_Y = U_4$.

The roll-pitch subsystem can be written as:

$$E_Y \dot{X}_Y = A_Y X + B_Y u_Y$$

$$y_Y = C_Y X + D_Y u_Y \quad (5.36)$$

where:

$$A_Y = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}; \quad B_Y = \begin{bmatrix} 0 \\ 1 \end{bmatrix}; \quad C_Y = \begin{bmatrix} 1 & 0 \end{bmatrix};$$

$$D_Y = [0]; \quad E_Y = \begin{bmatrix} 1 & 0 \\ 0 & I_z \end{bmatrix}$$

The parameter $\rho_Y$ that is varying is: $\rho_Y = [I_z]$. Its varying range is in table 5.1.

In order to express the system in polytopic form, matrices $A_Y, B_Y, C_Y, D_Y, E_Y$ can be decomposed as:

$$A_Y = A_{Y_0} + \rho_Y A_{Y_1}$$

$$B_Y = B_{Y_0} + \rho_Y B_{Y_1}$$

$$C_Y = C_{Y_0} + \rho_Y C_{Y_1}$$

$$D_Y = D_{Y_0} + \rho_Y D_{Y_1}$$

$$E_Y = E_{Y_0} + \rho_Y E_{Y_1}$$

where:

$$A_{Y_0} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}; \quad A_{Y_1} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}; \quad B_{Y_0} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}; \quad B_{Y_1} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_{Y_0} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}; \quad C_{Y_1} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}; \quad D_{Y_0} = [0]; \quad D_{Y_1} [0]$$

$$E_{Y_0} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}; \quad E_{Y_1} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$
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Weight functions for Yaw $H_\infty$ controller are chosen as following:

\[
W_{u3} = \frac{0.25}{s + 0.2}
\]
\[
W_{p3} = \frac{s^3 + 0.03s^2}{s^3 + 12000s^2 + 11300000s + 1000}
\]

The norm of LPV $H_\infty$ Yaw subsystem is $\gamma_Y = 0.0188$

**Remark 5.2.** The controller is synthesized by using the command `hinfgs` of the robust control toolbox in Matlab as in Remark 5.1. This controller minimizes the closed-loop quadratic $H_\infty$ performance from reference signal $\psi_{ref}$ to $z^T = [z_5 \ z_6]$ signal.

### 5.4.3 Simulation results and discussions

In this section, the trajectory for the quadcopter to follow is defined as follows: first, the quadcopter goes up 2m on altitude, and then follows a square of 8m of side on $x$ and $y$ (Fig. 5.13). The yaw angle $\psi$ is not change during the flight.

The mass declines in two manners: gradually and abruptly. A test for the robustness of the proposed controller with respect to step and impulse disturbances is also considered. In particular, we consider wind as a source of disturbances.

The first type of disturbances involves a series of wind impulses with velocity $V_w = 7 \cdot i + 7 \cdot j + 7 \cdot k$ at 5s, 15s, 25s, 35s, 45s, 55s, 65s, 75s, 85s, respectively. The second type of disturbances comes from two wind steps with velocity $V_w = 1 \cdot i + 1 \cdot j + 1 \cdot k$ from 15s to 25s, and from 55s to 65s, respectively. Both types of disturbances are demonstrated in the fourth plot of Fig. (5.6). In this figure, the changes of mass, moments of inertia wrt to the three axis $x, y, z$ are shown in the first, second, and third plot, respectively.

![Figure 5.6: Variation of mass and moments of inertia and disturbances.](image)

In the gradual mass reduction simulation, the mass reduces gradually from 0.93 [kg] to 0.6 [kg]) in a period from 0s to 90s, as shown in the first plot of Fig. (5.6). At each point
the mass changes, the recalculated moments of inertia are shown in the second and third plots of the same figure.

In the abrupt mass reduction simulation, the mass declines abruptly at 10s (from 0.93 [kg] to 0.83 [kg]), at 20s (from 0.83 [kg] to 0.73 [kg]), at 45s (from 0.73 [kg] to 0.63 [kg]), and at 60s (from 0.63 [kg] to 0.6 [kg]), as shown in the first plot of Fig. (5.6). At each point the
mass changes, the recalculated moments of inertia are shown in the second and third plots of the same figure.
5.4.4 Comments on the simulation results

From the simulation results, we can see that the quadcopter is stable and tracks the predefined trajectory well under the variation of dynamic parameters and the presence of disturbances.
Fig. (5.8) shows that the roll, pitch and yaw angles track their designated trajectories. The error of roll, pitch and yaw are shown in Fig. (5.10). The maximum error is about 10 degrees only when the system is disturbed by high impulse disturbances, but it quickly drops to near 0 degree.

Fig. (5.7) shows the references and responses in $x$, $y$, and $z$. Fig. (5.9) shows the errors with respect to $x$, $y$, and $z$ and $\psi$.

In both instances of mass variation, the quadcopter still tracks the predefined trajectory even under step and impulse disturbances, as shown in Fig. (5.12) and Fig. (5.13).

In many cases, the states of the system are not available or too expensive for measuring, the measured outputs are noisy, or some disturbances acting to the system are unable to be measured. Consequently, observers are used to overcome this difficulties.

5.5 Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)

The problems of observing the state and the unknown inputs of a linear/non-linear dynamic system is a challenging problem and have been studied since the 1970’s [41][170][64]. An observer can play the aims of a virtual (software) sensor. This virtual sensor is aimed to estimate system parameters that are difficult or impossible to measure such as states or unknown inputs (faults, disturbances,...).

Several extensions for observer have been considered for linear and nonlinear systems after the result proposed by D.G. Luenberger in [140]. The state estimation error is expressed as a system which is free from any unknown input in decoupling approach. The full rank conditions ensure the necessary and sufficient conditions for the existence of the observer.
5.5. Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)

For the second approach, both state vector and unknown input are estimated at the same time under the assumption that unknown inputs are part of the state vector \( \rho \). In [223], a nonlinear disturbance observer-based backstepping controller is developed for attitude, altitude, and position control subject to some external disturbances. The stability analysis of the nonlinear disturbance observer is successfully done using the Lyapunov stability theory. In [9], a sliding mode control scheme is proposed for a quadrotor in the presence of an exogenous disturbance. The authors propose a disturbance observer to reject the effect of the unknown disturbance on the quadrotor by using a nonlinear sliding mode surface.

For a quadrotor, it is really important to determine the external forces and moments such as the force of the wind. However, forces and moments are really difficult to measure during the operation. Therefore, an alternative solution is to use an observer. Furthermore, the mass and moments of inertia of UAVs are important impacting parameters to take into account, however, for some reasons, the mass is varying. For example, in applications for spraying pesticides, the mass and moments of inertia of flying equipment will vary slowly over time. Meanwhile, with the job of transporting goods, the mass and moments of inertia of aircraft change abruptly. Mass change implies the changes of moments of inertia. Because of the changes of quadcopter’s parameter (mass and moments of inertia), the fixed structure observer might not be working precisely. These issues can be addressed using LPV UIOs [100].

The aim of this section is to design an LPV Unknown Input Observer for the attitude of a mass-varying quadcopter, which can estimate the external torques. The feature of this proposed LPV UIO is that its structure can vary along with the changes of the mass and moments of inertia. To begin with, the design of UIO for the LPV system is considered. The existence conditions of the LPV UIO for the LPV system is studied, and then the gains of the UIO are calculated by resolving LMIs, which ensure the convergence to zero of the state estimation error and the unknown input estimation error. Then, from the dynamic of the attitude of the mass-varying quadcopter, the LPV altitude controller is generated. Finally, an LPV UIO is designed for the altitude system of the mass-varying quadcopter.

5.5.1 Problem formulation

This sub-section aims to design an LPV UIO for a LPV system which structure is expressed by

\[
\begin{align*}
\dot{x}(t) &= A(\rho(t))x(t) + B(\rho(t))u(t) + E(\rho(t))d(t) \\
y(t) &= Cx(t)
\end{align*}
\]  

where \( x(t) \in \mathbb{R}^n \), \( u(t) \in \mathbb{R}^{nu} \), \( d(t) \in \mathbb{R}^{nd} \), and \( y(t) \in \mathbb{R}^y \) are the state vector, the control input, the unknown input, and the output of the system, respectively. The matrices \( A(\cdot) \), \( B(\cdot) \), and \( E(\cdot) \) are varying parameters with appropriate dimensions, and \( C \) is a matrix of constants. \( \rho^T(t) = (\rho_1, ..., \rho_{n_\rho}) \) represents the vector of \( n_\rho \) time-varying parameters which are sufficiently smooth and bounded which means that \( \rho(t) \) is an element of \( \Theta \), a hyper-rectangle defined by

\[
\Theta = \left\{ \rho(t) \in \mathbb{R}^{n_\rho} \mid \rho_1 \in [\underline{\rho}_1, \overline{\rho}_1], ..., \rho_{n_\rho} \in [\underline{\rho}_{n_\rho}, \overline{\rho}_{n_\rho}] \right\}
\]  

where \( \underline{\rho}_i \) and \( \overline{\rho}_i \), \( i = 1, ..., n_\rho \) define the lower and upper bounds of the varying parameter \( \rho_i(t) \).
For sake of simplicity, in what follows we put $\Delta(\rho(t))$ as $\Delta_\rho$ where $\Delta$ is a matrix depending on the varying parameter $\rho(t)$. In addition, system (5.37) can be free of input by defining an auxiliary system in the form

$$\begin{align*}
\dot{s}(t) &= A_\rho s(t) + B_\rho u(t) \\
y_s(t) &= Cs(t)
\end{align*}$$

(5.39)

Define the errors $z(t) = x(t) - s(t)$ and $y_z(t) = y(t) - y_s(t)$, the new dynamics

$$\begin{align*}
\dot{z}(t) &= A_\rho z(t) + E_\rho d(t) \\
y_z(t) &= Cz(t)
\end{align*}$$

(5.40)

can be obtained from the systems in (5.37) and (5.39), which are free from the known input $u(t)$. Thus, after estimating the state $\hat{x}(t)$, the real state $\hat{x}(t)$ is obtained by the equation

$$\hat{x}(t) = \hat{z}(t) + s(t)$$

(5.41)

Consequently, the problem of designing the LPV UIO for LPV system in (5.37) is transformed to the problem of designing the LPV UIO for the LPV system without the known input depicted in (5.40).

**Definition 5.1.** The system (5.37) is said to be uniformly strongly algebraically observable with respect to the parameter $\rho(t)$ if there exists positive integers $k_y$, $k_u$ and $k_p$ such that $\rho^{(j)}(t) \in \Theta_j, j = 0, \ldots, k_p$ the state of the system (5.37) can be expressed as a vector function of the outputs, the inputs, the parameters and their time derivatives up to a finite orders

$$x(t) = F \left( y(t), \ldots, y^{(k_y)}, u(t), \ldots, u^{(k_u)}, \rho(t), \ldots, \rho^{(k_p)} \right)$$

(5.42)

Assume also that the time derivatives of the parameters belong to the compact sets defined by

$$\Theta_j = \left\{ \rho^{(j)}(t) \in \mathbb{R}^{k_p} \left| \rho_1^{(j)}(t) \in [\underline{\rho}_{ij}, \bar{\rho}_{ij}], \ldots, \rho_{n_p}^{(j)}(t) \in [\underline{\rho}_{n_p ij}, \bar{\rho}_{n_p ij}] \right. \right\}$$

(5.43)

where $\underline{\rho}_{ij}$ and $\bar{\rho}_{ij}, i = 1, \ldots, n_p$ define the lower and upper bounds of the $j$th derivative of the varying parameter $\rho_i(t)$.

**Definition 5.2.** Given the system (5.37), the number $r$ is called the relative degree of the output $y(t)$ with respect to the unknown input $d(t)$ if the unknown input $d(t)$ appears in the equation of the $r^{th}$ time derivative of the output $\left. y^{(r)}(t) \right|$ and not in $y^{(k)}$ for $k < r$.

### 5.5.2 LPV UIO design for LPV system

Let us consider the LPV system in (5.40) where $y_z(t) \in \mathbb{R}^{n_y}$ and $d(t) \in \mathbb{R}^{n_d}$. Suppose that, each output $y_{z_i}(t)$ has a relative degree $r_i$ where $i = 1, \ldots, n_y$ with respect to the unknown inputs. Thus, the vector of relative orders is given by $\left\{ r_1, r_2, \ldots, r_{n_y} \right\}$.

The matrices $E_\rho(\rho(t))$ and $C$ can be rewritten as $E_\rho(\rho(t)) = \left[ E_1 \rho \ E_2 \rho \ldots \ E_{n_d} \rho \right]$, $C = \left[ C_1 \ldots C_{n_y} \right]^T$.  


By differentiating \( r \) times the \( i^{th} \) output \( y_{zi}(t) \), one gets
\[
\begin{align*}
\dot{y}_{zi}(t) &= C_i z(t) \\
\ddot{y}_{zi}(t) &= C_i A_{\rho} z(t) \\
\dddot{y}_{zi}(t) &= \left(M_{i\rho}^1 A_{\rho} + M_{i\rho}^1 \right) z(t) \\
\dddot{y}_{zi}(t) &= \left(M_{i\rho}^2 A_{\rho} + M_{i\rho}^2 \right) z(t) \\
\dddot{y}_{zi}(t) &= \left(M_{i\rho}^3 A_{\rho} + M_{i\rho}^3 \right) z(t) \\
&\vdots \\
\dddot{y}_{zi}(t) &= \left(M_{i\rho}^n A_{\rho} + M_{i\rho}^n \right) z(t) + M_{i\rho}^n d_i(t)
\end{align*}
\]
From \((5.44a)\) to \((5.44e)\), the output time derivatives are obtained in matrix form as follows
\[
Y(t) = M_{\rho} z(t) + \Gamma_\rho d(t)
\]
where
\[
Y(t) = \begin{bmatrix}
y_1^{(r_1)}(t) \\
y_2^{(r_2)}(t) \\
\vdots \\
y_{ny}^{(r_{ny})}(t)
\end{bmatrix}, M_{\rho}(t) = \begin{bmatrix}
M_{1\rho}^1 \\
M_{2\rho}^1 \\
\vdots \\
M_{ny\rho}^1
\end{bmatrix}
\]
and
\[
\Gamma_\rho = \begin{bmatrix}
M_{(r_1-1)\rho}^1 E_{\rho}^1 & M_{(r_1-1)\rho}^1 E_{\rho}^2 & \cdots & M_{(r_1-1)\rho}^1 E_{\rho}^{n_d} \\
M_{(r_2-1)\rho}^1 E_{\rho}^1 & M_{(r_2-1)\rho}^1 E_{\rho}^2 & \cdots & M_{(r_2-1)\rho}^1 E_{\rho}^{n_d} \\
\vdots & \vdots & \ddots & \vdots \\
M_{(r_{ny}-1)\rho}^1 E_{\rho}^1 & M_{(r_{ny}-1)\rho}^1 E_{\rho}^2 & \cdots & M_{(r_{ny}-1)\rho}^1 E_{\rho}^{n_d}
\end{bmatrix}
\]
Consequently, the observer for \((5.40)\) is proposed in the form
\[
\begin{align*}
\dot{\hat{z}}(t) &= (A_\rho - Q_\rho M_\rho - L_\rho C) \hat{z}(t) + Q_\rho Y(t) + L_\rho y_z(t) \\
\dot{d}(t) &= \Gamma_\rho^{-1}(Y(t) - M_\rho \hat{z}(t))
\end{align*}
\]
where \(Q_\rho\) and \(L_\rho\) are to be determined.

**Theorem 5.1.** The system \((5.46)\) is an observer for the system \((5.40)\) if the following conditions are satisfied:

- The matrix \(\Gamma\) is full column rank \(\forall \rho \in \Theta\)
- The pair \((A_\rho - Q_\rho M_\rho, C)\) is detectable \(\forall \rho \in \Theta\), where \(Q_\rho = E \Gamma^{-1}\) if \(n_y = n_d\), and \(Q_\rho = E \Gamma^\dagger\) if \(n_y > n_d\), \(\Gamma^\dagger\) is the pseudo inverse of \(\Gamma\)
- The parameter varying matrix \((A_\rho - Q_\rho M_\rho - L_\rho C)\) is stable \(\forall \rho \in \Theta\)
Proof. The state estimation error is defined as $e(t) = z(t) - \hat{z}(t)$ and the unknown input estimation error $e_d(t) = d(t) - \hat{d}(t)$. The derivative of the error is

$$
\dot{e}(t) = \dot{z}(t) - \dot{\hat{z}}(t) = A_\rho z(t) + E_\rho d(t) - (A_\rho - Q_\rho M_\rho - L_\rho C) \dot{z}(t) - Q_\rho Y(t) - L_\rho y_z(t) - (A_\rho - Q_\rho M_\rho - L_\rho C) \epsilon(t) + (E_\rho - Q_\rho \Gamma_\rho) d(t) \tag{5.47}
$$

Under the condition that the matrix $\Gamma$ is full column rank, $\Gamma^{\dagger} (\Gamma^{-1}$ if $\Gamma$ is square) exists and ensures that $E_\rho - Q_\rho \Gamma_\rho = 0$, the state estimation dynamics becomes

$$
\dot{e}(t) = (A_\rho - L_\rho C - Q_\rho M_\rho) e(t) \tag{5.48}
$$

From the condition that the pair $(A_\rho - Q_\rho M_\rho, C)$ is detectable $\forall \rho \in \Theta$, the gain matrix $L_\rho$ can be computed in order to ensure the asymptotic stability of the system (5.48) which ensures that state of the observer converges asymptotically to the state of the system. The unknown input estimation can be computed as follows

$$
e_d(t) = d(t) - \hat{d}(t) = -\Gamma^{-1}_\rho M_\rho e_z(t) \tag{5.49}
$$

which ensures that $e_d$ converges towards 0 when $e_z(t) \to 0$. The structure of UIO in (5.46) is depicted in figure 5.14.

\section{5.5.3 Convergence analysis and LMI formulation}

From (5.48) and (5.49), we have

$$
\begin{align*}
\dot{e}_z(t) &= (A_\rho - Q_\rho M_\rho - L_\rho C) e_z(t) \\
e_d(t) &= -\Gamma^{-1}_\rho M_\rho e_z(t)
\end{align*} \tag{5.50}
$$

![Figure 5.14: Unknown Input Observer for dynamic system](image-url)
5.5. Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)

In order to derive LMI conditions for design purpose, we next transform the matrices $A_\rho$, $Q_\rho$, $M_\subset$, and $\Gamma_\rho$ in a polytopic form where the parameters $\rho(t) \in \Theta$, one obtains

$$
A_\rho = \sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) A_i
$$

$$
Q_\rho = \sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) Q_i
$$

$$
M_\rho = \sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) M_i
$$

$$
\Gamma_\rho = \sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) \Gamma_i
$$

(5.51)

$$
\forall \rho(t) \in \Theta \text{ and } \mu_i(\rho(t)) \text{ satisfy the convex sum property}
$$

$$
\sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) = 1, \ 0 \leq \mu_i(\rho(t)) \leq 1, \ i = 1, \ldots, 2^n_\rho, \ \forall \rho(t) \in \Theta
$$

(5.52)

Thus, the gain matrix $L_\rho$ can be determined as

$$
L_\rho = \sum_{i=1}^{2^n_\rho} \mu_i(\rho(t)) L_i
$$

(5.53)

Consequently, the state estimation error dynamics (5.48) can be expressed by

$$
\dot{e}_z(t) = \sum_{i=1}^{2^n_\rho} \sum_{j=1}^{2^n_\rho} \mu_i(\rho(t)) \mu_j(\rho(t)) (A_j - Q_i M_j - L_j C) e_z(t)
$$

(5.54)

Standard LMI for stability can be obtained using a quadratic Lyapunov function in the form

$$
V(e_z(t)) = e_z^T(t) X e_z(t), X = X^T > 0
$$

(5.55)

The time derivative of the Lyapunov function is

$$
\dot{V}(e_z(t)) = e_z^T(t) X e_z(t) + e_z^T(t) X \dot{e}_z(t)
$$

(5.56)

Finally, the derivative of the Lyapunov function $V(e_z(t))$ in (5.56) can be rewritten as

$$
\dot{V}(e_z(t)) = e_z^T(t) [A_\rho X + X A_\rho - (Q_\rho M_\rho)^T X + X Q_\rho M_\rho - C^T K_\rho^T - K_\rho C] e_z(t)
$$

(5.57)

where $K_\rho = L_\rho C$.

After computing the time derivative of the Lyapunov function $V(e_z(t))$ and by using the state estimation error dynamics (5.54) and the convex sum property of the weighting functions in (5.52), sufficient LMI conditions ensuring asymptotic stability are obtained as follows

$$
A_j^T X + X A_j - (Q_j M_j)^T X + X Q_j M_j - C^T K_j^T - K_j C < 0, \ i, j = 1 \ldots 2^n_\rho
$$

(5.58)

where the gains of the observer are obtained from the equation $L_i = X^{-1} K_i$. This solution ensures the convergence to zero of the state estimation error $e_z(t)$, and the unknown input estimation error $e_d(t)$. 

5.5.4 LPV UIO design

The proposed LPV Unknown input observer is based on Linear Matrix Inequality (LMI) methods. The resolvability of the resulting LMI conditions in this case is quite compromised due to the number of submodels. The more number of submodel is, the more is conservativeness of LMI conditions. In order to reduce this number, we adopt here a simpler model. We assume that the quadcopter is symmetric and $I_x = I_y$. We also assume that to the altitude sub-model of the quadcopter is disturbed the torques $d(t) = \begin{bmatrix} d_{\phi} & d_{\theta} & d_{\psi} \end{bmatrix}^T$ allowing to write:

\[
\begin{cases}
\dot{\phi} = \frac{I_y - I_x}{I_x} \dot{\theta} \dot{\psi} - \frac{J_{\Omega}}{I_x} \dot{\theta} \dot{\psi} + \frac{I}{I_x} u_2 + \frac{1}{I_x} d_{\phi} \\
\dot{\theta} = \frac{I_y - I_x}{I_x} \dot{\phi} \dot{\psi} + \frac{J_{\Omega}}{I_x} \dot{\phi} \dot{\psi} + \frac{I}{I_x} u_3 + \frac{1}{I_x} d_{\theta} \\
\dot{\psi} = \frac{1}{I_x} \ddot{u}_1 + \frac{1}{I_x} \ddot{d}_{\psi}
\end{cases}
\]  

(5.59)

We can see that, the dynamic equation of the yaw angle does not contain Euler angles or their derivatives. Thus, the dynamic of quadcopter attitude can be decomposed into two subsystems, the roll-pitch subsystem is the first two equations and the yaw subsystem is the third equation of (5.59).

5.5.4.1 LPV UIO for Roll-Pitch

The system differential equations for $\varphi$ and $\theta$ are rewritten from (5.59) as

\[
\begin{cases}
\dot{\varphi} = \dot{\varphi} \\
\dot{\theta} = \dot{\theta} \\
\ddot{\varphi} = \frac{I_y - I_x}{I_x} \dot{\varphi} \dot{\psi} - \frac{J_{\Omega}}{I_x} \dot{\varphi} \dot{\psi} + \frac{I}{I_x} u_2 + \frac{1}{I_x} d_{\varphi} \\
\ddot{\theta} = \frac{I_y - I_x}{I_x} \dot{\varphi} \dot{\psi} + \frac{J_{\Omega}}{I_x} \dot{\varphi} \dot{\psi} + \frac{I}{I_x} u_3 + \frac{1}{I_x} d_{\theta}
\end{cases}
\]  

(5.60)

LPV system for roll pitch can be obtained from system differential equation (5.60) as

\[
\begin{cases}
\dot{x}_1(t) = A_{1_{\rho_1}} x_1(t) + B_{1_{\rho_1}} u_1(t) + E_{1_{\rho_1}} d_1(t) \\
y_1(t) = C_1 x_1(t)
\end{cases}
\]  

(5.61)

where varying parameters, state, output, known input, and unknown input are respectively $\rho_1(t) = \begin{bmatrix} \rho_{11} & \rho_{12} \end{bmatrix}^T = \begin{bmatrix} \frac{1}{I_x} (I_y - I_x) \dot{\varphi} \dot{\psi} - \frac{J_{\Omega}}{I_x} \dot{\varphi} \dot{\psi} \end{bmatrix}^T$, $x_1(t) = \begin{bmatrix} \varphi & \theta & \dot{\varphi} & \dot{\theta} \end{bmatrix}^T$, $y_1(t) = \begin{bmatrix} \varphi & \theta & \dot{\varphi} & \dot{\theta} \end{bmatrix}^T$, $u_1(t) = \begin{bmatrix} U_2 & U_3 \end{bmatrix}$; $d_1(t) = \begin{bmatrix} d_{\varphi} & d_{\theta} \end{bmatrix}^T$ and the system matrices are:

\[
A_{1_{\rho_1}} = \begin{bmatrix} 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & -\rho_{12} & 0 \\
1 & 0 & 0 & 0 \end{bmatrix}; B_{1_{\rho_1}} = \begin{bmatrix} 0 & 0 \\
0 & 0 \\
0 & 0 \\
0 & 0 \end{bmatrix} \\
C_1 = \begin{bmatrix} 0 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0 \end{bmatrix}; E_{1_{\rho_1}} = \begin{bmatrix} 0 & 0 \\
0 & 0 \\
\rho_{11} & 0 \\
0 & \rho_{11} \end{bmatrix}
\]

(5.62)

Define an auxiliary system in the form

\[
\begin{cases}
\dot{s}_1(t) = A_{1_{\rho_1}} s_1(t) + B_{1_{\rho_1}} u_1(t) \\
y_{s_1}(t) = C_1 s_1(t)
\end{cases}
\]  

(5.63)
Define the errors \( z_1(t) = x_1(t) - s_1(t) \) and \( y_{z_1}(t) = y_1(t) - y_{s_1}(t) \), the new dynamics

\[
\begin{align*}
\dot{z}_1(t) &= A_{1p_1} z_1(t) + E_{1p_1} d_1(t) \\
y_{z_1}(t) &= C_{1z_1}(t)
\end{align*}
\]  
(5.64)

can be obtained from the systems in (5.61) and (5.63), which are free from the known input \( u_1(t) \). Thus, after estimating the state \( \hat{z}_1(t) \), the real state \( \hat{x}_1(t) \) is obtained by the equation \( \hat{x}_1(t) = \hat{z}_1(t) + s_1(t) \).

Take the derivative of the output \( y_{z_1} = \begin{bmatrix} y_{z_{11}} & y_{z_{12}} & y_{z_{13}} & y_{z_{14}} \end{bmatrix} \) as in (5.44a) to (5.44e), one obtains:

\[
\begin{align*}
y_{z_{11}}^{(2)} &= \rho_{12}\tau_4 + \rho_{11}d_\varphi \\
y_{z_{12}}^{(2)} &= -\rho_{12}\tau_3 + \rho_{11}d_\varphi \\
y_{z_{13}}^{(1)} &= \rho_{12}\tau_4 + \rho_{11}d_\varphi \\
y_{z_{14}}^{(1)} &= -\rho_{12}\tau_3 + \rho_{11}d_\varphi
\end{align*}
\]  
(5.65)

Consequently, the relative degrees \( r_i \) of the \( i^{th} \) output, \( i = 1, \ldots, 4 \) respectively are \( r_{11} = 2, r_{12} = 2, r_{13} = 1, \) and \( r_{14} = 1 \).

Following the defined vector \( y_1(t) = \begin{bmatrix} y_{z_{11}}^{(2)} & y_{z_{12}}^{(2)} & y_{z_{13}}^{(1)} & y_{z_{14}}^{(1)} \end{bmatrix}^T = \mathcal{M}_{1p_1} z_1(t) + \Gamma_{1p_1} d_1(t) \) in (5.45), one obtains

\[
\Gamma_{1p_1} = \begin{bmatrix} \rho_{11} & 0 & 0 & 0 \\
0 & \rho_{11} & 0 & 0 \\
0 & 0 & \rho_{11} & 0 \\
0 & 0 & 0 & \rho_{11} \end{bmatrix}
\]  
(5.66)

which satisfies the full column rank condition and its pseudo-inverse is given by

\[
\Gamma_{1p_1}^\dagger = \begin{bmatrix} \frac{1}{2\rho_{11}} & 0 & 0 & 0 \\
0 & \frac{1}{2\rho_{11}} & 0 & 0 \\
0 & 0 & \frac{1}{2\rho_{11}} & 0 \\
0 & 0 & 0 & \frac{1}{2\rho_{11}} \end{bmatrix}
\]  
(5.67)

The unknown input decoupling matrix \( Q_{1p_1} \) is then given by

\[
Q_{1p_1} = \begin{bmatrix} 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\frac{1}{2} & 0 & \frac{1}{2} & 0 \\
0 & \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}
\]  
(5.68)

We can verify that the pair \( (A_{1p_1} - Q_{1p_1}\mathcal{M}_{1p_1}, C_1) \) is detectable, where the matrix \( \mathcal{M}_{1p_1} \) and \( A_{1p_1} - Q_{1p_1}\mathcal{M}_{1p_1} \) are respectively

\[
\mathcal{M}_{1p_1} = \begin{bmatrix} 0 & 0 & 0 & \rho_{12} \\
0 & 0 & -\rho_{12} & 0 \\
0 & 0 & 0 & \rho_{12} \\
0 & 0 & -\rho_{12} & 0 \end{bmatrix}
\]  
(5.69)

\[
A_{1p_1} - Q_{1p_1}\mathcal{M}_{1p_1} = \begin{bmatrix} 0_2 & I_2 \\
0_2 & 0_2 \end{bmatrix}
\]

Finally, the gain matrix \( L_{1p} \) of the UIO can be calculated such that the parameter varying matrix \( A_{1p_1} - Q_{1p_1}\mathcal{M}_{1p_1} - L_{1p_1}C_2 \) is stable \( \forall \rho_{11}, \rho_{12} \in \Theta_{p_1} \) by solving LMI's as in (5.58), where \( \Theta_{p_1} \) is the hyper-rectangle for \( \rho_{11} \) and \( \rho_{12} \) which is defined in (5.38).
5.5.4.2 Linear Parameter Varying (LPV) Unknown Input Observer (UIO) for Yaw

The system differential equations for $\psi$ are rewritten from (5.59) as

$$
\begin{align*}
\dot{\psi} &= \dot{\phi} \\
\ddot{\psi} &= \frac{1}{I_z} U_4 + \frac{1}{I_z} d_{\psi}
\end{align*}
$$

(5.70)

The LPV system for yaw can be obtained from system differential equation (5.70) as

$$
\begin{align*}
\dot{x}_2(t) &= A_{2_{\rho_2}} x_2(t) + B_{2_{\rho_2}} u_2(t) + E_{2_{\rho_2}} d_2(t) \\
y_2(t) &= C_2 x_2(t)
\end{align*}
$$

(5.71)

where varying parameters, state, output, known input, and unknown input are respectively

$$
\rho_2(t) = \begin{bmatrix} \rho_{21} \end{bmatrix} \quad x_2(t) = \begin{bmatrix} \psi & \dot{\psi} \end{bmatrix}^T \quad y_2(t) = \begin{bmatrix} \psi & \dot{\psi} \end{bmatrix}^T \quad u_2(t) = [U_4] \quad d_2(t) = [d_{\psi}]
$$

and the system matrices are

$$
\begin{bmatrix} A_{2_{\rho_2}} \quad B_{2_{\rho_2}} \quad E_{2_{\rho_2}} \quad C_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 \end{bmatrix}
$$

(5.72)

Define an auxiliary system in the form

$$
\begin{align*}
\dot{s}_2(t) &= A_{2_{\rho_2}} s_2(t) + B_{2_{\rho_2}} u_2(t) \\
y_{s_2}(t) &= C_2 s_2(t)
\end{align*}
$$

(5.73)

Define the errors $z_2(t) = x_2(t) - s_2(t)$ and $y_{z_2}(t) = y_2(t) - y_{s_2}(t)$, the new dynamics

$$
\begin{align*}
\dot{z}_2(t) &= A_{2_{\rho_2}} z_2(t) + E_{2_{\rho_2}} d(t) \\
y_{z_2}(t) &= C_2 z_2(t)
\end{align*}
$$

(5.74)

can be obtained from the systems in (5.71) and (5.73), which are free from the known input $u_2(t)$. Thus, after estimating the state $\hat{z}_2(t)$, the real state $\hat{x}_2(t)$ is obtained by the equation $\hat{x}_2(t) = \hat{z}_2(t) + s_2(t)$.

Take the derivative of the output $y_{z_2} = \begin{bmatrix} y_{z_21} & y_{z_22} \end{bmatrix}^T$ as in (5.44a) to (5.44e), one obtains:

$$
\begin{align*}
y_{z_21}^{(2)} &= \rho_{21} d_{\psi} \\
y_{z_21}^{(1)} &= \rho_{21} d_{\psi}
\end{align*}
$$

(5.75)

Consequently, the relative degrees $r_i$ of the $i^{th}$, $i = 1, 2$ output respectively are $r_{21} = 2$, $r_{22} = 1$.

Following the defined vector $Y_2 = \begin{bmatrix} y_{z_21}^{(2)} & y_{z_21}^{(1)} \end{bmatrix}^T$ in (5.45), one obtains

$$
\Gamma_{2_{\rho_2}} = \begin{bmatrix} \rho_{21} \\
\rho_{21} \end{bmatrix}
$$

(5.76)

which satisfies the full column rank condition and the pseudo-inverse exists and given by

$$
\Gamma_{2_{\rho_1}} = \begin{bmatrix} \frac{1}{\rho_{21}} & \frac{1}{\rho_{21}} \end{bmatrix}
$$

(5.77)
5.5. Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)

The unknown input decoupling matrix $Q_{2\rho}$ is then given by

$$Q_{2\rho} = \begin{bmatrix} 0 & 0 \\ 1 & 2 \end{bmatrix}$$ (5.78)

We can verify that the pair $\left( A_{2\rho} - Q_{2\rho} M_{2\rho}, C_2 \right)$ is detectable, where the matrix $M_{2\rho}$ and $A_{2\rho} - Q_{2\rho} M_{2\rho}$ are respectively

$$M_{2\rho} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}; \quad A_{2\rho} - Q_{2\rho} M_{2\rho} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$ (5.79)

Finally, the gain matrix $L_{2\rho}$ of the UIO can be calculated such that the parameter varying matrix $A_{2\rho} - Q_{2\rho} M_{2\rho} - L_{2\rho} C_2$ is stable $\forall \rho_21 \in \Theta_{\rho_2}$ by solving LMIs as in (5.58), where $\Theta_{\rho_2}$ is the hyper rectangle for $\rho_21$ which is defined in (5.38).

**Remark 5.3.** As we can see the system matrices in (5.62) and (5.72), the state repeats exactly the output of the system. It means that we use the information of the measured outputs to estimate itself. This observer helps to recover the real state of the system efficiently in case of disturbed outputs. Furthermore, this observer allows us to estimate the unknown input that affects the system. The information about unknown inputs is really useful for improving the quality of quadcopter control.

**Remark 5.4.** Suppose that each actuator thrust Laplace transform is given by

$$T_i(s) = \frac{K_i}{1 + \tau_i s} V_i(s), \quad i = 1, 2, 3, 4$$ (5.80)

where $T_i$ is the Laplace transform of the thrust $T_i(t)$, $V_i$ is the pulse width modulation (PWM) voltage, $K_i$ is the armature gain, and $\tau_i$ is the time constant of the $i^{th}$, $i = 1, \ldots, 4$ rotor. The corresponding differential equation is

$$\dot{T}_i = -\frac{1}{\tau_i} T_i + \frac{K_i}{\tau_i} v_i$$ (5.81)

We also known that, the thrust $T_i(t)$ is a function of the rotor speed

$$T_i(t) = k_f \omega_i^2$$ (5.82)

where $k_f$ is the constant coefficient.

Consequently, based on the PWM applied to each rotor, the rotor speed $\omega_i$ can be estimated. Thus, the residual speed $\Omega_r = \omega_2 + \omega_4 - \omega_1 - \omega_3$ can also be estimated.

**Remark 5.5.** Due to Remark 5.3 and Remark 5.4, one can see that all the varying parameters for LPV UI observers designed in 5.5.4.1 and 5.5.4.2 can be measured.

5.5.4.3 LPV UIO for Altitude

The system differential equations for altitude $z$ are rewritten from (3.54c) as

$$\begin{aligned}
\dot{z} &= \dot{\theta} \\
\ddot{z} &= \frac{\cos \varphi \cos \theta}{m} U_1 - g + \frac{1}{m} d_z
\end{aligned}$$ (5.83)
Chapter 5. Nonlinear robust control and state estimation of UAVs

The unknown input decoupling matrix \( Q_{3p3} \) is then given by

\[
Q_{3p3} = \begin{bmatrix}
0 & 0 \\
0 & 0
\end{bmatrix}
\]  

(5.91)

Finally, the gain matrix \( L_{3p3} \) of the UIO can be calculated such that the parameter varying matrix \( A_{3p3} - Q_{3p3} M_{3p3} - L_{3p3} C_3 \) is stable \( \forall \rho_3 \in \Theta_{p3} \) by solving LMI as in (5.58), where \( \Theta_{p3} \) is the hyper-rectangle for \( \rho_3 \) which is defined in (5.38).
5.5. Simulation results

The quadcopter parameters for simulation are listed in the following table 5.2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m )</td>
<td>Quadcopter mass</td>
<td>2.0</td>
<td>Kg</td>
</tr>
<tr>
<td>( l )</td>
<td>Arm length</td>
<td>0.23</td>
<td>m</td>
</tr>
<tr>
<td>( b )</td>
<td>Thrust coefficient</td>
<td>( 7.73213 \times 10^{-6} )</td>
<td>N \cdot s^2</td>
</tr>
<tr>
<td>( d )</td>
<td>Drag coefficient</td>
<td>( 1.27513 \times 10^{-6} )</td>
<td>N \cdot m \cdot s^2</td>
</tr>
<tr>
<td>( I_x, I_y )</td>
<td>Inertia on x and y axis</td>
<td>0.0142</td>
<td>Kg \cdot m^2</td>
</tr>
<tr>
<td>( I_z )</td>
<td>Inertia on z axis</td>
<td>0.0267</td>
<td>Kg \cdot m^2</td>
</tr>
<tr>
<td>( J_r )</td>
<td>Rotor inertia</td>
<td>( 8.5 \times 10^{-4} )</td>
<td>Kg \cdot m^2</td>
</tr>
<tr>
<td>( \omega_i )</td>
<td>Rotor speed</td>
<td>[0, 500]</td>
<td>rad \cdot s^{-1}</td>
</tr>
</tbody>
</table>

Based on quadcopter’s parameters in table 5.2 and the definition of varying parameters in subsections 5.5.4.1 and 5.5.4.2, the ranges of varying parameters are shown in the table 5.3

![Figure 5.15: Variations of mass and moments of inertia](image-url)
For simulation, the mass of quadcopter is varying abruptly between 5s and 25s from 2 (kg) to 1.12 (kg). Along with the quadcopter’s mass variation, the moments of inertia $I_x, I_y, I_z$ around the three axes $I_x = I_y \in [0.0119 \quad 0.0142] \ [kg \cdot m^2]$, and $I_z \in [0.0223 \quad 0.0267] \ [kg \cdot m^2]$ abruptly change as in Fig. 5.15.

The actual and estimated states of the quadcopter for the simulation with the step reference trajectories of $\varphi, \theta$, and $\psi$ are shown in Fig. 5.16 and Fig. 5.17, while the actual and estimated disturbances (random disturbances) and their differences are shown in Fig. 5.18. The estimated state and disturbances converge to the actual values in about 7s.
5.5. **Attitude/Altitude Linear Parameter Varying (LPV) Unknown Input Observer (UIO)**

In Fig. 5.19, 5.20, and 5.21 are shown the results for the case of step reference signals and constant disturbances.

Different simulations using multiple reference (impulse, step, random, and sin) and different types of disturbances (impulse, step, random, and sin) have shown a satisfactory performance of the proposed UIO.
The same simulations for slow variation of mass are also conducted, the state and unknown inputs are also well estimated.

5.6 Attitude/Altitude \( LPV \) \( H_\infty \) State feedback Controller

5.6.1 System model and problem statement

The aim of this section is to propose a simple design procedure of \( LPV \) state feedback for the attitude/altitude stabilization problem of the mass-varying quadrotor aircraft. In our context, the main objective of the state feedback synthesis is to handle the mass, moments of inertia and rotors velocity variations which are assumed to be measured. This is achieved using a \( LPV \) formalism which allows to obtain a Takagi-Sugeno (TS) model with 16 submodels depending on the extremal values of the varying parameters. The controller is then synthesized on the basis of a 16 sub-models system. It allows us to perform both a reference trajectory tracking and disturbance rejection for attitude/altitude control of a mass-varying quadcopter. First, an augmented state which includes the integration of the trajectory errors for improving tracking control is computed. Next, to penalize the control inputs of the attitude/altitude system, weight functions are also added to the previous augmented system. Then, an \( LPV \) \( H_\infty \) state-feedback controller is designed by solving a set of Linear Matrix Inequality (LMI) obtained from the Bounded Real Lemma and LMI region characterization. Simulations are conducted for several types of disturbances (sine, impulse, step, and random) and variations (slow and abrupt) of mass and moments of inertia. The reference path (sine, impulse, and step) is well-followed showing the ability of the design method to handle different performance objectives.

The remainder of the section is organized as follows: Subsection 5.6.1.1 presents the dynamical model of the quadcopter and some preliminary concepts for designing the objective of the multi-objective controller. Subsection 5.6.3 is dedicated for designing the \( LPV \) state feedback controller for the attitude/altitude of the quadcopter. The controller is practically synthesized in subsection 5.6.4, while simulation results are presented in subsection 5.6.5. Some remarks on the simulation results are shown in subsection 5.6.6.

5.6.1.1 Quadrotor model

A quadcopter is a helicopter which consists of a rigid cross frame equipped with four rotors as shown in Fig. 5.22. Its four rotors generate four independent thrusts. In order to avoid the yaw drift due to the reactive torques, the quadropter aircraft is configured such that the set of rotors \( M_2, M_4 \) (left-right) revolve clockwise (CW) at angular speeds \( \omega_2 \) and \( \omega_4 \), respectively generating thrusts of \( \tau_2 \) and \( \tau_4 \), while the pair of rotors \( M_1, M_3 \) (front-rear) rotates at angular speeds \( \omega_1 \) and \( \omega_3 \) in counterclockwise (CCW) direction generating thrusts of \( \tau_1 \) and \( \tau_3 \). The direction of rotation of the rotors are fixed (i.e., \( \omega_i \geq 0, i \in \{1,2,3,4\} \)). The forward/backward, left/right and the yaw motions are achieved through a differential control strategy of the thrust generated by each rotor.

If a yaw motion is desired, the thrust of one set of rotors has to be reduced and the thrust of the other set are increased while maintaining the same total thrust to avoid an up (down)
motion. Therefore, the yaw motion is then realized in the direction of the induced reactive torque. Besides, forward (backward) motion is achieved by pitching in the desired direction by increasing the rear (front) rotor thrust and decreasing the front (rear) rotor thrust to maintain the total thrust. Finally, a sideways motion is achieved by rolling in the desired direction by increasing the left (right) rotor thrust and decreasing the right (left) rotor thrust to maintain the total thrust.

Let \( I = \{e_x, e_y, e_z\} \) denotes an inertial frame, and \( A = \{e_1, e_2, e_3\} \) denotes a frame rigidly attached to the aircraft as shown in Fig. 5.22.

The mathematical model of the quadcopter was generated by the techniques of both Euler-Newton [30] and Euler-Lagrange [31], given as follows:

\[
\begin{align*}
\dot{x}_c &= (\sin \psi \sin \varphi + \cos \psi \sin \theta \cos \varphi) \frac{U_1}{I_{\text{e}}} \\
\dot{y}_c &= (\sin \psi \sin \varphi - \cos \psi \sin \theta \cos \varphi) \frac{U_1}{I_{\text{e}}} \\
\dot{z}_c &= (\cos \theta \cos \varphi) \frac{U_1}{I_{\text{e}}} - g \\
\dot{\varphi} &= \frac{I_y - I_z}{I_x} \dot{\theta} \psi - \frac{J_{\text{e}} \Omega_r}{I_y} \dot{\theta} + \frac{1}{I_x} U_2 \\
\dot{\theta} &= \frac{I_z - I_x}{I_y} \dot{\varphi} \psi + \frac{J_{\text{e}} \Omega_r}{I_y} \dot{\phi} + \frac{1}{I_y} U_3 \\
\dot{\psi} &= \frac{I_x - I_y}{I_z} \dot{\varphi} \theta + \frac{1}{I_z} U_4
\end{align*}
\]

(5.93)

where \( m \) denotes the mass of the quadcopter, \((x_c, y_c, z_c)\) are the three positions of the center of mass, \((\varphi, \theta, \psi)\) are the three Euler angles, \(I_x, I_y, I_z\) are the moments of inertia w.r.t the three axis \(x, y,\) and \(z\) respectively; \(J_r\) is the moment of inertia of the propellers, \(l\) represents the distance from the rotors to the center of mass of the quadrotor aircraft. \(\Omega_r\) is the overall residual propeller angular speed, \(b\) and \(d\) are thrust and drag coefficients. The quadcopter’s inputs are: the thrust force \((U_1)\), three torques (roll torque \((U_2)\), pitch torque \((U_3)\), and yaw torque \((U_4)\)). The force and torques are related to the rotor speed as follows:

\[
\begin{align*}
U_1 &= k_f \left( \omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2 \right) = \sum_{i=1}^{4} T_i \\
U_2 &= k_f \left( \omega_1^2 - \omega_2^2 \right) = T_4 - T_2 \\
U_3 &= k_f \left( \omega_3^2 - \omega_1^2 \right) = T_3 - T_1 \\
U_4 &= k_z \left( -\omega_2^2 + \omega_3^2 - \omega_4^2 \right) = (T_2 + T_4) - (T_1 + T_3)
\end{align*}
\]

(5.94)

and

\[
\Omega_r = \omega_1 - \omega_2 + \omega_3 - \omega_4
\]

(5.95)

where \(\omega_i\) for \(i = 1, 2, 3, 4\) denotes the \(i\)-th rotor velocity, and \(T_i\) for \(i = 1, 2, 3, 4\) are the thrust generated by the \(i\)-th rotor and the thrust \(T_i(t)\) is a function of the rotor speed defined by

\[
T_i(t) = k_f \omega_i^2
\]

(5.96)

where \(k_f\) and \(k_z\) are the constant coefficients.

The first three equations of the system differential equations in (5.93) denote the translational movement, while the last three present the rotational movement of the quadcopter. We restrict the purpose of this section to the attitude tracking. Thus, the equations related to the longitudinal and lateral motions of the quadcopter in (5.93) are removed.
5.6.1.2 Actuator model

Adopting an actuator model has twofold. First of them is to reflect the low pass filtering of each actuator with a time constant $\kappa_i, i = 1, 2, 3, 4$. The second allows us to prevent the $B$ matrix of the obtained state-space representation to be parameter dependent. Each actuator thrust Laplace transform is given by

$$T_i(s) = \frac{K_i}{1 + \kappa_is}V_i(s), \quad i = 1, 2, 3, 4$$

(5.97)

$T_i$ is the Laplace transform of the thrust $T_i(t)$, $V_i$ is the pulse width modulation (PWM) voltage applied to rotor $i$, and $K_i$ is the armature gain.

The corresponding differential equation is

$$\dot{T}_i = -\frac{1}{\kappa_i}T_i + \frac{K_i}{\kappa_i}V_i$$

(5.98)

**Remark 5.6.** Based on the PWM applied to each rotor, the rotor speed $\omega_i$ can be estimated. Thus, the residual speed $\Omega_r = \omega_2 + \omega_4 - \omega_1 - \omega_3$ can also be estimated.

5.6.1.3 Simplified model

The previous model still exhibits too many parameters and its polytopic representation will involve at least $2^6$ sub-models. If one considers control synthesis using LMI methods, the solvability of the resulting LMI conditions in this case is quite compromised due to conservativeness of conditions which will request the common stabilization of a huge number of sub-models. In order to reduce this number, we adopt here a simplified model. In particular, suppose that $I_x = I_y$ and $\varphi$ and $\theta$ are small so that $\cos\varphi\cos\theta \approx 1$.

We also assume that the attitude/altitude subsystem of the quadcopter is affected by torques $d_\varphi, d_\theta, d_\psi$, and force $d_z$ allowing to write:

$$\begin{bmatrix}
\ddot{\varphi} \\
\ddot{\theta} \\
\ddot{\psi} \\
\ddot{z}_c
\end{bmatrix} = \begin{bmatrix}
\frac{-Jx\Omega_r\varphi + \frac{1}{I_x}(T_4 - T_2) + \frac{1}{I_x}d_\varphi}{Jx} \\
\frac{Jx\Omega_r\varphi + \frac{1}{I_x}(T_3 - T_1) + \frac{1}{I_x}d_\theta}{Jy} \\
\frac{(T_3 + T_2) - (T_1 + T_4)}{(T_3 + T_1)} + \frac{1}{I_z}d_\psi \\
\frac{T_1 + T_2 + T_3 + T_4}{m} + \frac{1}{m}d_z - g
\end{bmatrix}$$

(5.99)

Note that $g$ is also the disturbance to the system. Then the disturbances can be written in the vector form as $d(t) = [d_\varphi, d_\theta, d_\psi, d_z, g]^T$.

Then, the LPV model of attitude/altitude sub-system in (5.93) is performed as:

$$\dot{x}(t) = A(I_x, I_z, \Omega_r, m)x(t) + Bu(t) + E(I_x, I_z, \Omega_r, m)d(t)$$

(5.100)
where state $x = (\varphi, \theta, \psi, z_c, \dot{\varphi}, \dot{\theta}, \dot{\psi}, \dot{z}_c, T_1, T_2, T_3, T_4)^T$ has twelve components, the control input vector is composed of the four motor voltages $u = (v_1, v_2, v_3, v_4)^T$, and the system matrices $A(I_x, I_z, \Omega_r, m)$, $B(I_x, I_z, \Omega_r, m)$, and $E(I_x, I_z, \Omega_r, m)$ are

$$
A(I_x, I_z, \Omega_r, m) = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ 0_{8 \times 4} & B_\ast \\ 0_{4 \times 5} & E_\ast \end{bmatrix}
$$

where

$$A_{11} = [0_{12 \times 4}]; \quad A_{12} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -I_x - I_z \dot{\psi} + J_r I_x \Omega_r & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}
$$

$$A_{13} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -l/I_x & 0 & l/I_x \end{bmatrix}
$$

$$B_\ast = \begin{bmatrix} K_1/\kappa_1 & 0 & 0 & 0 \\ 0 & K_2/\kappa_2 & 0 & 0 \\ 0 & 0 & K_3/\kappa_3 & 0 \\ 0 & 0 & 0 & K_4/\kappa_4 \end{bmatrix}; \quad E_\ast = \begin{bmatrix} 1/I_x & 0 & 0 & 0 & 0 \\ 0 & 1/I_x & 0 & 0 & 0 \\ 0 & 0 & 1/I_z & 0 & 0 \\ 0 & 0 & 0 & 1/m & -1 \end{bmatrix}
$$

Note that, as described above, the system matrix $B$ is time invariant.

Thus a TS model with 16 sub-models could be obtained depending on the extremal values of the parameters. This representation is called nonlinear sector approximation \cite{214}. In fact,
The matrices can thus obtain a LPV model depending on four parameters, the moment of inertia with respect to x axis $I_x \in \left[ I_x, \bar{I_x} \right]$, the moment of inertia with respect to z axis $I_z \in \left[ I_z, \bar{I_z} \right]$, the residual velocity $\Omega_r \in \left[ \bar{\Omega_r}, \Omega_r \right]$, and the mass $m \in \left[ m, \bar{m} \right]$ of the quadcopter.

Then a sixteen sub-models TSS system is achieved

$$\dot{x}(t) = \sum_{i=1}^{16} \mu_i \left( \bar{A}_i \dot{x}(t) + Bu(t) + \bar{E}_i d(t) \right) \quad (5.102)$$

where $\mu_i \geq 0, 1 \leq i \leq 16, \sum_{i=1}^{16} \mu_i = 1$ and

$$\begin{align*}
\mu_1(\rho(t)) &= m_{11} m_{21} m_{31} m_{41}; & \mu_2(\rho(t)) &= m_{11} m_{21} m_{32} m_{42}; \\
\mu_3(\rho(t)) &= m_{11} m_{22} m_{31} m_{41}; & \mu_4(\rho(t)) &= m_{11} m_{22} m_{32} m_{42}; \\
\mu_5(\rho(t)) &= m_{11} m_{22} m_{32} m_{41}; & \mu_6(\rho(t)) &= m_{11} m_{22} m_{31} m_{42}; \\
\mu_7(\rho(t)) &= m_{11} m_{22} m_{32} m_{41}; & \mu_8(\rho(t)) &= m_{11} m_{22} m_{31} m_{42}; \\
\mu_9(\rho(t)) &= m_{11} m_{22} m_{31} m_{42}; & \mu_10(\rho(t)) &= m_{12} m_{21} m_{31} m_{42}; \\
\mu_{11}(\rho(t)) &= m_{12} m_{21} m_{32} m_{41}; & \mu_{12}(\rho(t)) &= m_{12} m_{21} m_{32} m_{42}; \\
\mu_{13}(\rho(t)) &= m_{12} m_{22} m_{31} m_{41}; & \mu_{14}(\rho(t)) &= m_{12} m_{22} m_{31} m_{42}; \\
\mu_{15}(\rho(t)) &= m_{12} m_{22} m_{32} m_{41}; & \mu_{16}(\rho(t)) &= m_{12} m_{22} m_{32} m_{42};
\end{align*}$$

with

$$\begin{align*}
m_{11}(\rho(t)) &= \frac{\bar{\rho}_1 - \rho_1}{\bar{\rho}_1 - \rho_1}; & m_{12}(\rho(t)) &= 1 - m_{11}; \\
m_{21}(\rho(t)) &= \frac{\bar{\rho}_2 - \rho_2}{\bar{\rho}_2 - \rho_2}; & m_{22}(\rho(t)) &= 1 - m_{21}; \\
m_{31}(\rho(t)) &= \frac{\bar{\rho}_3 - \rho_3}{\bar{\rho}_3 - \rho_3}; & m_{32}(\rho(t)) &= 1 - m_{31}; \\
m_{41}(\rho(t)) &= \frac{\bar{\rho}_4 - \rho_4}{\bar{\rho}_4 - \rho_4}; & m_{42}(\rho(t)) &= 1 - m_{41}.
\end{align*}$$

The matrices $\bar{A}_i, 1 \leq i \leq 16$ are obtained from

$$\begin{align*}
\bar{A}_1 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \bar{\rho}_3, \bar{\rho}_4 \right); & \bar{A}_2 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \bar{\rho}_3, \bar{\rho}_4 \right); \\
\bar{A}_3 &= A \left( \bar{\rho}_1, \rho_2, \bar{\rho}_3, \bar{\rho}_4 \right); & \bar{A}_4 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \bar{\rho}_3, \bar{\rho}_4 \right); \\
\bar{A}_5 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \rho_3, \bar{\rho}_4 \right); & \bar{A}_6 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \bar{\rho}_3, \rho_4 \right); \\
\bar{A}_7 &= A \left( \bar{\rho}_1, \rho_2, \rho_3, \bar{\rho}_4 \right); & \bar{A}_8 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \rho_3, \rho_4 \right); \\
\bar{A}_9 &= A \left( \bar{\rho}_1, \bar{\rho}_2, \rho_3, \bar{\rho}_4 \right); & \bar{A}_{10} &= A \left( \bar{\rho}_1, \bar{\rho}_2, \rho_3, \rho_4 \right); \\
\bar{A}_{11} &= A \left( \bar{\rho}_1, \rho_2, \rho_3, \rho_4 \right); & \bar{A}_{12} &= A \left( \bar{\rho}_1, \rho_2, \rho_3, \rho_4 \right); \\
\bar{A}_{13} &= A \left( \rho_1, \bar{\rho}_2, \rho_3, \bar{\rho}_4 \right); & \bar{A}_{14} &= A \left( \rho_1, \bar{\rho}_2, \rho_3, \rho_4 \right); \\
\bar{A}_{15} &= A \left( \rho_1, \bar{\rho}_2, \bar{\rho}_3, \rho_4 \right); & \bar{A}_{16} &= A \left( \rho_1, \bar{\rho}_2, \bar{\rho}_3, \rho_4 \right).
\end{align*}$$
The output vector $y = \begin{bmatrix} \varphi & \theta & \psi & z \end{bmatrix}^T$ is constituted by the quadrotor attitude/altitude position which are obtained from

$$y = Cx + Du$$

(5.104)

where

$$C = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}$$

and

$$D = \begin{bmatrix} 0 & 0 \end{bmatrix}_{4x4}$$

**Remark 5.7.** Suppose that the quadcopter is attached with $n$ objects $o_1, \ldots, o_n$, and the mass of quadcopter and objects are $m_q, m_{o_1}, \ldots, m_{o_n}$ respectively. Therefore, the mass of the system consists of the quadcopter and $n$ objects can be easily calculated by the equation $m = m_q + m_{o_1} + \ldots + m_{o_n}$. When $o_i$ - the $i$-th object is detached from the quadcopter for $i = n, \ldots, 1$, the remaining mass of the system can be recalculated.

Depending on the mass and shape of each object, ones can calculate its moments of inertia around the axes passing through its center of mass. When attaching these objects to the quadcopter, based on their shapes and positions with respect to the center of gravity $G$ of the quadcopter, their the moments of inertia with respect to the three axes $I_x, I_y, I_z$ of the quadcopter can be calculated. Thus the moment of inertia of the system which contains quadcopter and $n$ objects $o_1, \ldots, o_n$ relative to $I_x, I_y, I_z$ can be calculated.

Another online approach to estimate the geometric and inertia parameters of a multirotor aerial vehicle is already developed in [239].

**Remark 5.8.** From Remarks 5.6 and 5.7 one can see that all the varying parameters can be estimated in real time.
5.6.2 Preliminary concepts

Suppose the polytopic LPV system is of the form

\[
\begin{align*}
\dot{x}(t) &= A(\rho(t))x(t) + B_1(\rho(t))w(t) + B_2u(t) \\
z(t) &= C(\rho(t))x(t) + D_{11}(t)w(t) + D_{12}u(t) \\
x(0) &= x_0
\end{align*}
\]  

(5.105)

where \( x \in \mathbb{R}^n \) is the system state, \( u \in \mathbb{R}^m \) is the control input, \( w \in \mathbb{R}^p \) is the exogenous input, and \( z \in \mathbb{R}^q \) is the controlled output. The \( \rho \)-parameter dependent system matrices is defined as

\[
A(\rho(t)) = \sum_{i=1}^{N} \mu_i(\rho(t))A_i; \quad B_1(\rho(t)) = \sum_{i=1}^{N} \mu_i(\rho(t))B_{1i};
\]

\[
C_1(\rho(t)) = \sum_{i=1}^{N} \mu_i(\rho(t))C_{1i}; \quad D_{11}(\rho(t)) = \sum_{i=1}^{N} \mu_i(\rho(t))D_{11i},
\]

while \( B_2 \) and \( D_{12} \) are constant matrices.

The purpose of this section is to design a \( \text{LPV} \) state-feedback control law

\[
u(t) = \sum_{i=1}^{N} \mu_i(\rho(t))K_ix(t)
\]  

(5.106)

such that the following conditions are satisfied:

- The \( H_{\infty} \) norm of the system \((5.105)\) from \( w \) to \( z \) (as depicted in Fig. 5.23) is guaranteed to be smaller than some predefined value \( \gamma > 0 \) for tracking and disturbance rejection (robustness). This condition is guaranteed by the following Theorem 5.2 below

- Closed loop poles are placed in a predefined \( \text{LMI} \) region \([202]\) for ensuring the ability of fast and well-damped transient response. The closed-loop poles satisfy the condition

\[
\begin{align*}
\text{Re} \left( \lambda \left( A + B_2YX^{-1} \right) \right) &< -\alpha < 0 \\
\text{s.t} \quad 2\alpha X + He(A_iX + B_2Y_i) &< 0, i = 1, \ldots, N
\end{align*}
\]

(5.107)

where \( \text{Re}(\ast) \) defines the real part of the complex number \( \ast \).

**Theorem 5.2.** (Theorem 3.4.1 in \([46]\)) The \( \text{LPV} \) system \((5.105)\) is quadratically stabilizable using a state-feedback of the form \((5.106)\) if there exist a matrix \( X \in S^n_{++} \), matrices \( Y_i \in \mathbb{R}^{m \times n}, i = 1, \ldots, N \), and a scalar \( \gamma > 0 \) such that the \( \text{LMI} \)

\[
\begin{bmatrix}
He(A_iX + B_2Y_i) & (\ast)^T \\
B_{1i}^T & -\gamma I_p \\
C_iX + D_{12}Y_i & D_{11i}^T -\gamma I_q
\end{bmatrix} < 0
\]

(5.108)

hold for all \( i = 1, \ldots, N \). Moreover, the state-feedback control law given by \((5.106)\) with the matrices \( K_i = Y_iX^{-1} \) ensures that the \( L_2 \)-gain of the transfer \( w \rightarrow z \) is smaller than \( \gamma > 0 \) for all \( \mu : R_{\geq 0} \rightarrow \Lambda_N \).

Then the state-feedback control law given by \((5.106)\) with the matrices \( K_i = Y_iX^{-1} \) satisfy Theorem 5.2 and equation \((5.107)\) ensures that the \( L_2 \)-gain of the transfer \( w \rightarrow z \) is smaller than \( \gamma > 0 \) for all \( \mu : R_{\geq 0} \rightarrow \Lambda_N \) and the poles of the close loop system satisfy condition

\[
\text{Re} \left( \lambda \left( A + B_2YX^{-1} \right) \right) < -\alpha, \quad \alpha > 0.
\]
5.6.3 LPV Attitude State feedback controller design

In this subsection, we aim to design a $H_\infty$ LPV feedback control scheme for the attitude/altitude stabilization of the quadrotor aircraft.

First, the output $y = [\phi \theta \psi z_c]^T$ of the system must track $r = [\phi_{\text{ref}} \theta_{\text{ref}} \psi_{\text{ref}} z_{\text{ref}}]^T$, a reference trajectory. Therefore, to achieve these objectives, the outputs of the integrator are considered as extra state variables $x_e = [x_{\phi} x_{\theta} x_{\psi} x_z]^T$ as

$$
x_{\phi} = \int e_{\phi}(\delta) d\delta, \quad e_{\phi} = \phi_{\text{ref}} - \phi \\
x_{\theta} = \int e_{\theta}(\delta) d\delta, \quad e_{\theta} = \theta_{\text{ref}} - \theta \\
x_{\psi} = \int e_{\psi}(\delta) d\delta, \quad e_{\psi} = \psi_{\text{ref}} - \psi \\
x_z = \int e_z(\delta) d\delta, \quad e_z = z_{\text{ref}} - z_c
$$

(5.109)

Define the error signal $e = y - r$. The error signal $e$ can be rewritten in the matrix form as

$$
e = y - r = Cx - I_4 r
$$

(5.110)

Second, for penalizing the outputs $U_1, U_2, U_3, U_4$ of the system, the weight functions $W_{u_i}, i = 1, 2, 3, 4$ are added to the system as depicted in Fig. 5.24. The system matrices of weight functions $W_{u_i}, i = 1, 2, 3, 4$ are $A_{u_i}, B_{u_i}, C_{u_i},$ and $D_{u_i}$.

Then, the dynamic of all the weighting functions $W_{u_1}, W_{u_2}, W_{u_3}$ and $W_{u_4}$ can be constituted as

$$
\begin{align*}
\dot{x}_u &= A_u x_u + B_u u \\
y_u &= C_u x_u + D_u u \\
\end{align*}
$$

(5.111)

where $x_u = [x_{u_1} x_{u_2} x_{u_3} x_{u_4}]^T$ is the state, $u = [U_1 U_2 U_3 U_4]^T$ represents the input, $y_u = [z_1 z_2 z_3 z_4]^T$ is the outputs of weight functions, and the system matrices of the weight function in (5.111) can be deduced as follows:

$$
\Delta_u = \begin{bmatrix}
\Delta_{u_1} & 0 & 0 & 0 \\
0 & \Delta_{u_2} & 0 & 0 \\
0 & 0 & \Delta_{u_3} & 0 \\
0 & 0 & 0 & \Delta_{u_4}
\end{bmatrix}, \quad \Delta \in \{A, B, C, D\}
$$

The augmented system with the new states, weight functions is depicted in Fig. 5.24.

Define $w = [r^T d^T]^T$, $z = [y_u^T e^T]^T$, and $\tilde{x} = [x_e^T x_{\phi}^T x_{\theta}^T x_{\psi}^T]^T$ respectively as the exogenous input, exogenous output, and state of the augmented affine parameter-dependent. The affine parameter-dependent of the system differential equations in (5.100) with augmented states and weight functions can be regathered from (5.100), (5.104), (5.110), and (5.111) as follows:

$$
\begin{align*}
\dot{\tilde{x}} &= \sum_{i=1}^{16} \mu_i(\rho(t)) \left( \tilde{A}_i \tilde{x} + \tilde{B}_1 w + \tilde{B}_2 u \right) \\
z &= C_1 \tilde{x} + D_{11} w + D_{12} u \\
\end{align*}
$$

(5.112)
where
\[
\begin{align*}
\tilde{A}_i &= \begin{bmatrix} \tilde{A}_i & 0 & 0 \\ -C & 0 & 0 \\ 0 & 0 & A_u \end{bmatrix}; \tilde{B}_1 &= \begin{bmatrix} 0 & \tilde{E}_i \\ -I_4 & 0 \\ 0 & 0 \end{bmatrix}; \tilde{B}_2 &= \begin{bmatrix} \tilde{B}_i \\ 0 \\ B_u \end{bmatrix} \\
C_1 &= \begin{bmatrix} 0 & C_u \\ C & 0 \\ 0 & 0 \end{bmatrix}; D_{11} &= \begin{bmatrix} 0 & \cdots & 0 \\ \cdots & \cdots & \cdots \\ 0 & \cdots & \gamma I \end{bmatrix}; D_{12} &= \begin{bmatrix} D_u \\ \cdots \\ 0 \end{bmatrix}
\end{align*}
\]

The aim now is to design the \textbf{LPV} $H_\infty$ optimal state-feedback controller of the form
\[
\begin{align*}
u(t) &= \sum_{i=1}^{16} \mu_i(\rho(t))K_i(t) \\
\hat{x}(t) &= \sum_{i=1}^{16} \mu_i(\rho(t)) \left( (\tilde{A}_i + \tilde{B}_2K_i(t)) \hat{x}(t) + \tilde{B}_1w(t) \right)
\end{align*}
\]

making the closed-loop system
\[
\hat{x}(t) = \sum_{i=1}^{16} \mu_i(\rho(t)) \left( (\tilde{A}_i + \tilde{B}_2K_i(t)) \hat{x}(t) + \tilde{B}_1w(t) \right)
\]

robustly asymptotically stable.

Define the \textbf{LMI}s for $H_\infty$ optimal state-feedback controller for all \textbf{TS} sub model with common matrix $X$ and each $Y_i$ for each \textbf{TS} sub model based on Theorem 5.2 and poles location conditions in (5.107) as
\[
\begin{align*}
\minimize \gamma, X, Y_1, \ldots, Y_{16} \\
\text{subject to} \\
X &= X^T \succ 0 \\
He \left( \tilde{A}_iX + \tilde{B}_2Y_i \right) + \gamma I \succ 0 \\
He \left( \tilde{B}_1^T \right) &\succ 0 \\
He \left( C_1X + D_{12}Y_i \right) &\succ 0 \\
He \left( \tilde{A}_iX + \tilde{B}_2Y_i \right) &+ 2\alpha X \succ 0; \ i = 1..16
\end{align*}
\]

By solving the \textbf{LMI}s in (5.115), the optimal $H_\infty$ state feedback controller with the smallest attenuation level $\gamma > 0$ for the attitude/altitude sub system of the mass-varying quadcopter can be formulated as
\[
K(\rho) = \sum_{i=1}^{16} \mu_i(\rho(t))Y_iX^{-1}
\]

### 5.6.4 Practical controller design

We consider Takagi-Sugeno (TS) model where the mass varies in the interval interval $[m, \bar{m}]$ with $m = 1.12$ $(kg)$ and $\bar{m} = 2.0$ $(kg)$. The moments of inertia $I_x = I_y$ varies in the interval $[I_x, \bar{I}_x]$ with $I_x = 0.0119$ $(kg.m^2)$ and $\bar{I}_x = 0.0142$ $(kg.m^2)$. The moments of inertia $I_z$ varies in the interval $[I_z, \bar{I}_z]$ with $I_z = 0.0223$ $(kg.m^2)$ and $\bar{I}_z = 0.0267$ $(kg.m^2)$. The total residual angular speed $\Omega_r$ of motors varies in the interval $[\Omega_r, \bar{\Omega}_r]$ with $\Omega_r = -1000$ $[rad\cdot s^{-1}]$ and $\bar{\Omega}_r = 1000$ $[rad\cdot s^{-1}]$. The controller is designed using the procedure developed above.
5.6. Attitude/Altitude LPV $H_\infty$ State feedback Controller

The quadcopter parameters for simulation are listed in the following table 5.4. Based on the quadcopter’s parameters in table 5.4, and the definition of varying parameters in subsections 5.6.1.3, the ranges of varying parameters are shown in the table 5.5.
Table 5.4: Quadcopter parameters definition

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Name</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>Quad. mass</td>
<td>2.0</td>
<td>Kg</td>
</tr>
<tr>
<td>l</td>
<td>Arm length</td>
<td>0.23</td>
<td>m</td>
</tr>
<tr>
<td>b</td>
<td>Thrust coef.</td>
<td>$7.73213 \times 10^{-6}$</td>
<td>N.s²</td>
</tr>
<tr>
<td>d</td>
<td>Drag coef.</td>
<td>$1.27513 \times 10^{-4}$</td>
<td>N.m.s²</td>
</tr>
<tr>
<td>$I_x, I_y$</td>
<td>Inertia vs x, y</td>
<td>0.0142</td>
<td>Kg.m²</td>
</tr>
<tr>
<td>$I_z$</td>
<td>Inertia vs z</td>
<td>0.0267</td>
<td>Kg.m²</td>
</tr>
<tr>
<td>$J_r$</td>
<td>Rotor inertia</td>
<td>$8.5 \times 10^{-4}$</td>
<td>Kg.m²</td>
</tr>
<tr>
<td>$\omega_i$</td>
<td>Rotor speed</td>
<td>[0,500]</td>
<td>rad/s</td>
</tr>
<tr>
<td>$\tau_i$</td>
<td>Rotor time const</td>
<td>15</td>
<td>rad/s</td>
</tr>
<tr>
<td>g</td>
<td>Gravity accel.</td>
<td>9.81</td>
<td>m/s²</td>
</tr>
</tbody>
</table>

5.6.5 Testing scenario

In simulations, the mass of the quadcopter is varying abruptly between 5s and 25s from 2(kg) to 1.12(kg). Along with the quadcopter’s mass variation, the moments of inertia $I_x, I_y, I_z$ for $I_x = I_y \in [0.0119 \ 0.0142]$, and $I_z \in [0.0223 \ 0.0267]$ also abruptly change as in Fig. 5.25. Fig. 5.26 shows the responses of $\varphi, \theta, \psi$ and $z$ when the reference signals are impulses and the disturbances $d_\varphi, d_\theta, d_\psi$, and $d_z$ are impulses. Fig. 5.27 shows the responses of $\varphi, \theta, \psi$ and $z$ when the reference signals are random, the $z$ reference signal is impulse, and the disturbances $d_\varphi, d_\theta, d_\psi$, and $d_z$ are random. Fig. 5.28 shows the responses of $\varphi, \theta, \psi$ when the reference signals $\phi, \theta, \psi$ are, the $z$ reference signal is step, and the disturbances $d_\varphi, d_\theta, d_\psi$, and $d_z$ are also sine.

The simulation results suggest that the proposed controller works well for various reference signals (impulse, random, constant, and sine) and several types of disturbances (impulse, random, constant, and sine).

The same simulation for slow variation of mass is also conducted, the reference paths are also well-followed.

Table 5.5: Variation ranges of varying parameters

<table>
<thead>
<tr>
<th>$\rho_i, i = 1,2,3,4$</th>
<th>$\bar{\rho}_i, i = 1,2,3,4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_1$</td>
<td>47.09580</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>35.84230</td>
</tr>
<tr>
<td>$\rho_3$</td>
<td>0.5000</td>
</tr>
<tr>
<td>$\rho_4$</td>
<td>-74.1176</td>
</tr>
</tbody>
</table>
5.6. Attitude/Altitude LPV $H_\infty$ State feedback Controller

**Figure 5.25:** Variations of Mass, $I_x$, $I_y$, and $I_z$

**Figure 5.26:** Impulse references $\varphi$, $\theta$, $\psi$, impulse reference $z$, and impulse disturbances $d_{\varphi}$, $d_{\theta}$, $d_{\psi}$, $d_z$

**Figure 5.27:** Random references $\varphi$, $\theta$, $\psi$, impulse reference $z$, and random disturbances $d_{\varphi}$, $d_{\theta}$, $d_{\psi}$, $d_z$

**Figure 5.28:** Sine references $\varphi$, $\theta$, $\psi$, step reference $z$, and sine disturbances $d_{\varphi}$, $d_{\theta}$, $d_{\psi}$, $d_z$
5.6.6 Remarks on simulation results

This section addresses the problem of attitude/altitude control of a quadcopter. The focus is on handling mass, moments of inertia variation of the quadcopter according to the specific application of transporting different device types. By adding some additional state and weight functions, the linear parameter-dependent system is gathered. Thus the problem of reference tracking is formulated as $H_\infty$ state feedback. It is solved using the LMI conditions framework. The obtained controller is found to be able to follow the prescribed trajectory with a high level of performance.

Future works of this section could concern the observer-based controller for a mass-varying quadcopter.

5.7 LPV Static output feedback controller for Attitude/Altitude

The aim of this section is to propose a simple design procedure of static output feedback for quadrotor. The use of static output feedback controller simplifies greatly control law reading and implementation. However, the synthesis is known as a hard problem but some relaxation procedures allow to reduce conservatism. In our context, the main objective of the static output feedback synthesis is to handle the mass and rotors velocity variations which are assumed to be measured. This is achieved using a Takagi-Sugeno (TS) formalism which allows to obtain a linear parameter varying model in the form of a convex sum of submodels. The controller is then synthesized on the basis of a 4 submodels system.

The remainder of this section is organized as follows. Subsection 5.7.1 presents the classical quadrotor model which is simplified in order to obtain a TS model suitable for control synthesis. Subsection 5.7.2 is devoted to the reference model tracking problem setting and model adaptation. Thus, the controller is synthesized in subsection 5.7.3 while simulation results are presented in section 5.7.4. Some remarks on simulation results are shown in subsection 5.7.5.

5.7.1 More simplified model

The mathematical differential equations of attitude/Altitude system of quadcopter are rewritten as

$$\begin{align*}
\dot{\varphi} &= I_y - I_z \dot{\theta} \hat{\psi} - \frac{I_z \Omega_z}{I_y} \dot{\theta} + \frac{1}{I_y} U_2 \\
\dot{\theta} &= I_z - I_y \hat{\psi} \dot{\varphi} + \frac{I_z \Omega_z}{I_y} \hat{\varphi} + \frac{1}{I_y} U_3 \\
\dot{\psi} &= \frac{I_z - I_y}{I_z} \hat{\varphi} \dot{\theta} + \frac{1}{I_y} U_4 \\
\ddot{z}_c &= (\cos \theta \cos \varphi) \frac{U_1}{m} - g
\end{align*}$$

(5.117)

The previous model still exhibits too much parameters and its polytopic representation will involve $2^9$ submodels. If one considers control synthesis using Linear Matrix Inequalities methods, the resolvability of the resulting LMI conditions in this case is quite compromised due to conservativeness of conditions which will request the common stabilization of a huge number of submodels. In order to reduce this number, we adopt here a more simplified model.
By using the model of the actuator as given in remark 5.4 and the simplification that velocities are small such that the product of the velocities can be assumed to be zero, allowing to write:

\[
\begin{align*}
\ddot{\varphi} &= -\frac{J_r}{I_x} \dot{\Omega}_r + l \frac{T_1 - T_2}{I_x} \\
\dot{\theta} &= \frac{J_r}{I_y} \Omega_r + l \frac{T_1 - T_3}{I_y} \\
\ddot{\psi} &= (T_2 + T_4) - (T_1 + T_3) \\
\ddot{z}_c &= -g + \frac{V_1 + V_2 + V_3 + V_4}{I_z}
\end{align*}
\]

(5.118)

Gathering all the equations, one can establish the \textit{LPV} model

\[
\dot{x}(t) = A(m, \Omega_r) x(t) + B v(t) + Ed(t)
\]

(5.119)

where the state vector is has twelve components:

\[
x = \begin{bmatrix}
\varphi, \dot{\varphi}, \theta, \dot{\theta}, \psi, \dot{\psi}, z_c, \dot{z}_c, T_1, T_2, T_3, T_4
\end{bmatrix}^T
\]

the control input vector is composed of the four motor voltages

\[
v = \begin{bmatrix}
v_1, v_2, v_3, v_4
\end{bmatrix}^T
\]

the disturbance input is the Earth gravity

\[
d = g
\]

and the matrix \( A(m, \Omega_r) \) is given by

\[
A(m, \Omega_r) = \begin{bmatrix}
A_{11} & A_{12} & A_{13}
\end{bmatrix}
\]

(5.120)

while

\[
A_{11} = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\end{bmatrix};
A_{12} = \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\end{bmatrix};
A_{13} = \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & -\frac{1}{I_x} & 0 & \frac{1}{I_x} \\
0 & 0 & 0 & 0 \\
\frac{1}{I_y} & 0 & -\frac{1}{I_y} & 0 \\
0 & 0 & 0 & 0 \\
\frac{1}{I_x} & -\frac{1}{I_x} & -\frac{1}{I_x} & \frac{1}{I_x} \\
0 & 0 & 0 & 0 \\
\frac{1}{m_1} & \frac{1}{m_1} & \frac{1}{m_1} & \frac{1}{m_1} \\
\frac{1}{\tau_1} & 0 & 0 & 0 \\
0 & -\frac{1}{\tau_2} & 0 & 0 \\
0 & 0 & -\frac{1}{\tau_3} & 0 \\
0 & 0 & 0 & -\frac{1}{\tau_4}
\end{bmatrix}
\]

The main objective of the control design procedure is to synthesize a controller that could be scheduled according to mass, inertia and rotor speed variation. As it can be seen from
the simplified quadrotor model, it is linear of both parameters. In addition, parametrizing
the moment of inertia in the form \( J_i = \kappa_i m_i, (i = x, y, z) \), one can thus obtain a LPV
model depending on two parameters, the mass \( m \in [m_m, m_M] \) and the velocity \( \Omega_r \in [\Omega_m, \Omega_M] \).

Thus a Takagi-Sugeno model with four submodels could be obtained depending on the extremal
distances of the parameters. This representation is called nonlinear sector approximation [214]. In fact, defining \( \rho_1 = m \in [m_m, m_M] \) and \( \rho_2 = \frac{\Omega_r}{m} \in [\Omega_m m, \Omega_M m] \) a four submodels TS
system is achieved

\[
\dot{x}(t) = \left( \sum_{i=1}^{4} \mu_i(\rho(t)) \bar{A}_i \right) x(t) + Bu(t) + Ed(t)
\]

where \( \mu_i \geq 0, 1 \leq i \leq 4 \), \( \sum_{i=1}^{4} \mu_i = 1 \) and

\[
\mu_1 = m_{11}m_{21}, \quad \mu_2 = m_{11}m_{22}
\]

\[
\mu_3 = m_{12}m_{21}, \quad \mu_3 = m_{12}m_{22}
\]

with

\[
\begin{align*}
    m_{11} &= \frac{\rho_{1\text{max}} - \rho_1}{\rho_{1\text{max}} - \rho_{1\text{min}}}, & m_{12} &= 1 - m_{11} \\
    m_{21} &= \frac{\rho_{2\text{max}} - \rho_2}{\rho_{2\text{max}} - \rho_{2\text{min}}}, & m_{22} &= 1 - m_{21}
\end{align*}
\]

The matrices \( \bar{A}_i, 1 \leq i \leq 4 \) are obtained from

\[
\begin{align*}
    \bar{A}_1 &= A(m_m, \Omega_m) \\
    \bar{A}_2 &= A(m_m, \Omega_M) \\
    \bar{A}_3 &= A(m_M, \Omega_m) \\
    \bar{A}_4 &= A(m_M, \Omega_M)
\end{align*}
\]

Notice that the obtained model is an exact representation of the model of equation (5.119).
The obtained model is a continuous time model. However for implementation aspects and
when considering preview information, it is more convenient to consider it in discrete time
domain. In fact the preview information is only available at some sensor sample times.
Knowing that, the model is discretized using a simple Euler method, this leads to the discrete-
time state-space model with sample time of \( T = 0.05 \text{sec} \).

\[
\begin{align*}
    x(k+1) &= \left( \sum_{i=1}^{4} \mu_i(\rho(t)) \bar{A}_i \right) x(k) + Bu(k) + Ed(k) \\
    y(k) &= Cx(k)
\end{align*}
\]

where \( (A_i, B, E) = (I_{12} + TA_i, TB, TE) \)

The output vector is constituted by the quadrotor altitude and attitude position which are obtained from the matrix

\[
C = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]
5.7.2 Controller Design

The considered model has the gravity a constant disturbance input. In order to cancel it in the control design and to obtain a zero steady state error, one can take the difference operator on both sides of equation (5.122) which leads to:

$$\begin{cases}
\Delta x(k+1) = \left( \sum_{i=1}^{4} \mu_i(\rho(t)) \overline{A}_i \right) \Delta x(k) + B \Delta u(k) \\
\Delta y(k) = C \Delta x(k)
\end{cases} \quad (5.123)$$

We consider in this section the problem of reference signal tracking with preview information. The output signal $y(k)$ has to follow the predefined reference signal $r(k)$. Defining the error signal $e(k)$ as

$$e(k) = y(k) - r(k) \quad (5.124)$$

and writing the error dynamics, one can define the augmented plant with the augmented state vector $\tilde{x} = [e^T(k), \Delta x^T(k)]^T$ which reads

$$\begin{cases}
\tilde{x}(k+1) = \sum_{i=1}^{4} \mu_i(\rho(t)) \left( \tilde{A}_i \tilde{x}(k) + \tilde{B} \Delta u(k) + G_p \Delta r(k) \right) \\
e(k) = \tilde{C} \tilde{x}(k)
\end{cases} \quad (5.125)$$

where

$$\tilde{A}_i = \begin{bmatrix} I_4 & C \\ 0 & A_r \end{bmatrix}, \quad \tilde{B} = \begin{bmatrix} 0 \\ B \end{bmatrix}, \quad G_p = \begin{bmatrix} -I_4 \\ 0 \end{bmatrix}, \quad \tilde{C} = \begin{bmatrix} I_4 & 0 \end{bmatrix}$$

Suppose now that the reference signal values are known $n_p$ samples ahead. Let us define the vector

$$x_r(k) = \begin{bmatrix} \Delta r^T(k) & \cdots & \Delta r^T(k+n_p) \end{bmatrix}^T \quad (5.126)$$

and the matrix

$$A_r = \begin{bmatrix} 0 & I_4 & 0 & \cdots & 0 \\ 0 & 0 & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & I_4 \\ 0 & \cdots & \cdots & 0 & 0 \end{bmatrix}$$

The objective now is to embed the reference signal appearing in equation (5.125) into a state vector. This is achieved by defining the state vector

$$\hat{x}(k) = \begin{bmatrix} \tilde{x}^T(k) & \tilde{x}_r^T(k) \end{bmatrix}^T$$

which allows to obtain the augmented system

$$\begin{cases}
\tilde{x}(k+1) = \sum_{i=1}^{4} \mu_i(\rho(t)) \left( \tilde{A}_i \tilde{x}(k) + \tilde{B} \Delta u(k) \right) \\
y_p(k) = \tilde{C} \tilde{x}(k)
\end{cases} \quad (5.127)$$

where

$$\tilde{A}_i = \begin{bmatrix} \tilde{A}_i & G_p \\ 0 & A_r \end{bmatrix}, \quad \tilde{B} = \begin{bmatrix} \tilde{B} \\ 0 \end{bmatrix}, \quad \begin{bmatrix} I_q & C \\ I_{n_p q+q} \end{bmatrix}$$
The aim now is to design a static output feedback controller of the form

\[
\Delta u(k) = \left( \sum_{i=1}^{4} \mu_i(\rho(t))K_i \right)y_p(k)
\]

making the closed-loop system

\[
\hat{x}(k+1) = \sum_{i=1}^{4} \mu_i(\rho(t))\left( \hat{A}_i + \hat{B}K_i\hat{C} \right)\hat{x}(k)
\]

robustly asymptotically stable. Following the results provided in [128], given a scalar \( \beta \) and matrices \( Q, W \), if there exist \( P_i > 0, U_i, L_i, G_i, 1 \leq i \leq 4 \) such that

\[
\Pi_i \prec 0, \quad 1 \leq i \leq 4
\]
where
\[
\Pi_i = \begin{bmatrix}
-G_i - G_i^T + P_i & * & * \\
\hat{A}_i G_i + \hat{B}_i L_i Q & -P_i & * \\
\hat{C}_i G_i - U Q & \beta W^T L_i \hat{B}_T & \Theta
\end{bmatrix}
\]  

and \( \Theta = -\beta U W - \beta W^T U^T \), then the system (5.129) is robustly asymptotically stable, and the gain matrix can be obtained by
\[
K_i = L_i U^{-1}
\]

One can notice that this matrix gain involves the following components

\[
K_i = \begin{bmatrix}
K_{ei} & K_{yi} & K_{ri} (0) & \ldots & K_{ri} (n_p)
\end{bmatrix}
\]

thus the command increment is given by
\[
\Delta u(k) = K_e e(k) + K_y \Delta y(k) + \sum_{j=0}^{n_p} K_r(j) \Delta r(k+j)
\]

where
\[
K_e = \sum_{i=1}^{4} \mu_i K_{ei}, \quad K_y = \sum_{i=1}^{4} \mu_i K_{yi}, \quad K_r(j) = \sum_{i=1}^{4} \mu_i K_{ri}(j)
\]

and finally the control input is obtained from
\[
u(k) = K_e \sum_{j=0}^{n_p} e(k) + K_y y(k) + \sum_{j=0}^{n_p} K_r(j) r(k+j)
\]

5.7.3 Practical controller design

The LPV model is considered assuming that the mass varies in the interval \([m_m, m_M]\) with \(m_m = 1 \text{[kg]} \) and \(m_M = 2 \text{[kg]} \). The total propeller velocity is varying in the interval \([\Omega_m, \Omega_M]\) with \(\Omega_m = -0.2\) and \(\Omega_M = 0.2\). The controller is designed using the procedure developed above. The preview horizon is taken up to \(n_p = 5\) points.

5.7.4 Testing scenario

As stated in the introduction, this paper is concerned with the attitude/altitude control. It is then assumed that the reference values for the pitch, roll, yaw and attitude are provided by an external loop. The quadrotor is requested to follow a circular path while increasing its altitude from 5 \([m]\) to 10 \([m]\). The path is shown in Fig. 5.29. One can see that the reference path is well followed. This can be verified in the Fig. 5.30 where the absolute value does not exceed 0.1 \([m]\). The altitude reference is also well followed as presented in Fig. 5.31. This is also the case for the pitch angle in Fig. 5.32. The reference value set for the yaw angle is 0. This is reached in less than one second in Fig. 5.34. The same simulation is now conducted by increasing the quadrotor mass until 2 \([kg]\). The system responses in this case are shown in Fig. 5.35 to Fig. 5.38. The responses become more oscillatory but remain acceptable.
5.7.5 Comments on the simulation results

This section addresses the problem of attitude/altitude control of an UAV. The focus is put on handling mass variation of the UAV according to the specific application of transporting different device types. Following an incremental model simplification, a simple LPV model is obtained for the selected motions. Afterwards, a 4 submodels TS model is derived. Thus the problem of reference tracking is formulated for static output feedback. It is solved using LMI conditions framework. The obtained controller is found to be able to follow the prescribed trajectory with high level of performance. Future works will both concern the exploration of reactive path planning realization and fault tolerant control.
5.8 Conclusion

In this chapter, we have examined the control problem for quadrotor applied in [PA]. In these applications, the mass of the quadrotor changes over time leads to changes in dynamic parameters of quadrotor such as the moments of inertia change. First, if the states of the system are available (measured or estimated), a $H_\infty$ LPV controller was developed for a mass-varying quadrotors. Then, when states are not available, the LPV dynamic and static controllers have been designed. Then, this chapter also concern the Linear Parameter Varying (LPV) Unknown Input Observer (UIO) for the mass-varying quadrotor.

![Figure 5.37: Measured and reference values for the roll angle for added mass](image1)

![Figure 5.38: Measured and reference value for the yaw angle for added mass](image2)
This chapter is dedicated for simulation results. In the first section 6.1 the Coverage Path Planning (CPP) for disease detection and crops spraying are generated. The section 6.2 is for simulation results of controlling the quadrotor. First, we show the stabilization simulation results for quadrotor using Linear Parameter Varying (LPV) $H_\infty$ dynamic output feedback, LPV static output feedback, and LPV $H_\infty$ state feedback controllers in subsection 6.2.1. The LPV Unknown Input Observer (UIO) for the altitude/attitude of the quadrotor will be shown in subsection 6.2.2. Then, in the subsection 6.2.3 the full control of quadrotor to follow the predefined points is given. The conclusion and some remarks are in section 6.3.
6.1 Coverage Path Planning (CPP) simulations

6.1.1 Coverage Path Planning (CPP) for disease detection

Assume that we have a rectangular agricultural land as shown in figure 6.1. In this agricultural land, there are convex and concave obstacles (yellow polygons) and pest infestation plants (red dots). The positions of the obstacles are known in prior, while the locations of pests ridden areas are unknown.

**Scenario 1.** Our mission is to use UAVs to take pictures of the entire agricultural land so that the coordinates of the crop areas affected by pests can be determined.
Based on the proposed algorithm in Figure 6.3, first, it is necessary to define critical points (blue and red circles in Figure 6.3). Then from these critical points, the agricultural area is divided into cells as in Figure 6.4 by using the proposed algorithm on 4.3.2.1. In this case, the agricultural area is divided into four non-intersecting obstacle-free regions (as shown and numbered in Figure 6.4).

Using the path generation algorithm proposed in the 4.3.2.2 section, we will draw rectangles equal in size to the frame size that the camera-equipped on the UAV can capture. These rectangles should intersect in both the long and short sides (as shown in Figure 6.5) to ensure the completeness of coverage of the entire area.

In the rectangles, as shown in Figure 6.5, we see that there are a number of rectangles centered on the obstacles (Figure 6.6). These locations are the points that the UAV cannot reach. Therefore, only rectangles whose center is not on obstacles (Figure 6.7) are considered to create the motion trajectory for UAV.
Rectangles whose center is not on obstacles are grouped into other groups depending on which cells the center coordinates are. As shown in Figure 6.7, rectangles whose center is not on obstacles are grouped into four groups with different colors.

From the center coordinates of the rectangles of these groups, the boustrophedon paths for the UAV in each cell (as shown in Figure 6.8a) are generated ensuring that UAV does not collide with the obstacles while traveling along with the generated path.
6.1. Coverage Path Planning (CPP) simulations

Figure 6.7: Scenario 1
Infected area detection Image frames in obstacles free

(a) Boustrophedon path contains collision with obstacles

(b) Boustrophedon path without collision with obstacles

Figure 6.8: Scenario 1
Infected area detection Boustrophedon path in cells
Chapter 6. Simulation results

Figure 6.9: Scenario 1
Infected area detection Start Stop Points in cells

Figure 6.10: Scenario 1
IA detection paths for changing cells using PRM TSP

Figure 6.8a shows that there exists one path that collides the obstacle. Consequently, the PRM should be applied for the two points that form the segment that collides obstacle to find the shortest obstacle-free path between them.

The final generated boustrophedon trajectory is shown in Figure 6.8b, we see that in the Boustrophedon trajectory generated on each cell, there are two points $S_i$ and $E_i$ with $i = 1, 2, 3, 4$. These two points are the points where UAV enters or exits the cell. The entering and existing points $S_i$ and $E_i$ in cells are shown in Figure 6.9.

Using the improved TSP algorithm detailed in the subsection 4.3.2.4, we can find the trajectory to change between cells so that the travel distance of the UAV is the smallest as shown in the Figure 6.10.
Therefore, the moving trajectory of \( \text{UAV} \) is obtained as follows (as depicted on Figures 6.10 and 6.11): \( \text{UAV} \) starts at point \( \text{START} \), moves to point \( S_1 \), moves along the Boustrophedon trajectory in cell 1 to point \( E_1 \), moves to point \( E_2 \), moves along the Boustrophedon trajectory in cell 2 to point \( S_2 \), moves to point \( S_4 \), moves along the Boustrophedon trajectory in cell 4 to point \( E_4 \), moves to point \( S_4 \), moves along the Boustrophedon trajectory in cell 3 to point \( E_E \), moves to point \( \text{STOP} \).
6.1.2 Coverage Path Planning (CPP) for crops spraying

**Scenario 2.** In this section, we perform a simulation to apply pesticides to the entire pest-affected crop area identified in section 6.1.1.

Assume agricultural area with fault and concave obstacles (yellow polygons) and pest-infested crop areas (red spots) as shown in the Figure 6.12. The coordinates of the obstacles and the crop areas affected by pests are known, thanks to the previous study.

First, the agricultural areas affected by pests and diseases will be grouped into different classes using clustering as shown in Figure 6.13. In this simulation, the number of selected classes is 2. Therefore we see that the pests and diseases are divided into two groups (the dots have different colors in Figure 6.13).

As discussed in 4.4.2, there are two methods to create polygons that cover each class of infected crop points: minimal convex polygon (Figure 6.14) and boundary polygon (Figure 6.15). In the case boundary polygon, this is the smallest polygon which covers all given points. This polygon can be convex or concave. Meanwhile, in the case of minimal convex polygon, this is the smallest convex polygon containing all given points.

However, as shown in Figures 6.14 and 6.15, we see that these two polygons partially cover the obstacles. Therefore, in order to create an obstacle-free area, we can create new polygons that cover all the pests and diseases and obstacle-free as in Figures 6.16 and 6.17.
6.1. Coverage Path Planning (CPP) simulations

Next, the resulting polygons in Figures 6.16 and 6.17 are divided into the minimal number of convex polygons as in Figures 6.18 and 6.19.

**Remark 6.1.** For the purpose of clarity, the red and blue dots (infected areas) will not be shown in Figure 6.18 - Figure 6.24.
Using the proposed algorithm for trajectory generation in convex polygon in 4.4.3, the boustrophedon trajectories are generated on each convex generated polygons as in Figures 6.20 and 6.21.

Also in Figures 6.20 and 6.21, we see that in the Boustrophedon trajectory generated on each convex polygons, there are two points $S_i$ and $E_i$ with $i = 1, ..., 16$. These two points are the points where UAV enters or exits the convex polygon. The entering and exiting points $S_i$ and $E_i$ in cells are shown in Figures 6.22 and 6.23.
Therefore, the moving trajectory of UAV is obtained as follows (as depicted on Figures 6.24) UAV starts at point START, moves to point $E_4$, moves along the Boustrophedon trajectory.

Figure 6.22: Scenario 2
IA spraying minimal convex decomposition START STOP points

Figure 6.23: Scenario 2
IA spraying boundary decomposition START STOP points

Figure 6.24: Scenario 2
IA spraying paths for changing cells using prm tsp
in cell 4 to point $S_4$, moves to point $E_2$, moves along the Boustrophedon trajectory in cell 2 to point $S_2$, moves to point $E_1$, moves along the Boustrophedon trajectory in cell 1 to point $S_1$, moves to point $E_3$, moves along the Boustrophedon trajectory in cell 3 to point $S_3$, moves to point $S_5$, moves along the Boustrophedon trajectory in cell 5 to point $E_5$, moves to point $E_6$, moves along the Boustrophedon trajectory in cell 6 to point $S_6$, moves to point STOP.
6.2 Quadrotor Control simulations

6.2.1 Quadrotor stabilization

6.2.1.1 Linear Parameter Varying (LPV) $H_{\infty}$ state feedback controller

In this section, we simulate the reference tracking of the LPV $H_{\infty}$ state feedback altitude/attitude controller for a mass-varying quadcopter under disturbances. Due to the variation of the mass, the moments of inertia with respect to the three axes $x$, $y$, and $z$ are also changing. The mass can be changed abruptly or gradually.

- The disturbances $d_\varphi$, $d_\theta$, $d_\psi$, and $d_z$ to roll $\varphi$, pitch $\theta$, yaw $\psi$, and altitude $z$ of the quadcopter can be sinus, random, step, square wave, or constant.
- The reference signals for roll $\varphi$, pitch $\theta$, yaw $\psi$, and altitude $z$ can be of the form sinus, random, step, square wave, or constant.

The configuration of the LPV $H_{\infty}$ Altitude/Attitude State Feedback Controller for mass-varying quadcopter is shown in Figure 6.25.
Scenario 3. In this simulation:

- Simulation time is 30 (s)
- The mass is abruptly changes at 5 (s) from 2 (kg) to 1.65 (kg), at 10 (s) from 1.65 (kg) to 1.3 (kg), at 15 (s) from 1.3 (kg) to 1.18 (kg), and at 25 (s) from 1.18 (kg) to 1.12 (kg). Consequently, the moments of inertia also change abruptly at 5 (s), 10 (s), 15 (s), 25 (s) as shown in Figure 6.26.
- The reference signals $\varphi_{\text{ref}}$, $\theta_{\text{ref}}$, $\psi_{\text{ref}}$, and $z_{\text{ref}}$ (the first sub-figure of Figure 6.28) are:
  - $\varphi_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), max amplitude is 30 (deg), min amplitude is 0 (deg)
  - $\theta_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), max amplitude is 29 (deg), min amplitude is 0 (deg)
  - $\psi_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), max amplitude is 28 (deg), min amplitude is 0 (deg)
  - $z_{\text{ref}}$ is a square wave signal of frequency $1/5$ (Hz), max amplitude is 1.5 (m), min amplitude is 1 (m)
- The disturbances $d_\varphi$, $d_\theta$, $d_\psi$, and $d_z$ (the last four sub-figures of Figure 6.28) are:
  - $d_\varphi$ is a random signal, max amplitude is 2.1 (Nm), min amplitude is $-2.1$ (Nm)
  - $d_\theta$ is a random signal, max amplitude is 2.1 (Nm), min amplitude is $-2.1$ (Nm)
  - $d_\psi$ is a random signal, max amplitude is 2.1 (Nm), min amplitude is $-2.1$ (Nm)
  - $d_z$ is a square wave signal of frequency $1/4$ (Hz), max amplitude is 6 (N), min amplitude is $-6$ (N)
6.2. Quadrotor Control simulations

The last four sub-figures of the Figure 6.28 show the reference signals and responses of $\varphi$, $\theta$, $\psi$, and $z$ respectively. We can see that $\varphi$, $\theta$, $\psi$, and $z$ track the reference signals well even under disturbances and the changes of mass and moments of inertia. The response time for $\varphi$, $\theta$, $\psi$, and $z$ are small.

The last four sub-figures of the Figure 6.29 show the differences between the actual signal and reference signals of $\varphi$, $\theta$, $\psi$, and $z$. We can see that, these error signals tend to zero quickly.

The input signals $U_1$, $U_2$, $U_3$, and $U_4$ for the quadcopter are shown in Figure 6.27.
Scenario 4. In this simulation:

- **Simulation time is 30 (s)**

- The mass gradually changes from 2 (kg) to 1.12 (kg) over a period of time from 5 (s) to 25 (s). Consequently, the moments of inertia also gradually change over a period of time from 5 (s) to 25 (s) as shown in Figure 6.30.

- The reference signals $\varphi_{ref}$, $\theta_{ref}$, $\psi_{ref}$, and $z_{ref}$ (the first sub-figure of Figure 6.32) are:
  - $\varphi_{ref}$ is a constant signal, $\varphi_{ref} = 30$ (deg)
  - $\theta_{ref}$ is a step signal at 4 (s) from 0 (deg) to 29 (deg)
  - $\psi_{ref}$ is a step signal at 6 (s) from 0 (deg) to 28 (deg)
  - $z_{ref}$ is a constant signal, $z_{ref} = 1$ (m)

- The disturbances $d_\varphi$, $d_\theta$, $d_\psi$, and $d_z$ (the last four sub-figures of Figure 6.32) are:
  - $d_\varphi$ is a sine signal of frequency $1/6$ (Hz), maximum amplitude is 2.1 (Nm), minimum amplitude is 0 (Nm)
  - $d_\theta$ is a sine signal of frequency $1/6$ (Hz), maximum amplitude is 2.1 (Nm), minimum amplitude is 0 (Nm)
  - $d_\psi$ is a sine signal of frequency $1/6$ (Hz), maximum amplitude is 2.1 (Nm), minimum amplitude is 0 (Nm)
  - $d_z$ is a random signal, maximum amplitude is 3 (N), minimum amplitude is $-6$ (N)

---

**Figure 6.30**: Scenario 4

Mass, $I_x$, $I_y$, and $I_z$

LPV $H_\infty$ Alt/Att State Feedback Controller

**Figure 6.31**: Scenario 4

$U_1$, $U_2$, $U_3$, and $U_4$

LPV $H_\infty$ Alt/Att State Feedback Controller
6.2. Quadrotor Control simulations

The last four sub-figures of the Figure 6.32 show the reference signals and responses of $\phi$, $\theta$, $\psi$, and $z$ respectively.

We can see that $\phi$, $\theta$, $\psi$, and $z$ track the reference signals well even under disturbances and the changes of mass and moments of inertia. The response time for $\phi$, $\theta$, $\psi$, and $z$ are small.

The last four sub-figures of the Figure 6.33 show the differences between the actual signal and reference signals of $\phi$, $\theta$, $\psi$, and $z$. We can see that, these error signals tend to zero quickly.

The input signals $U_1$, $U_2$, $U_3$, and $U_4$ for the quadcopter are shown in Figure 6.31.
6.2.2 Quadrotor Unknown Input Observer (UIO)

To evaluate the effectiveness of the proposed Linear Parameter Varying (LPV) Unknown Input Observer (UIO), we conduct two types of simulation in this section. The first type of simulation concerns the UIO for the system without measurement noises in subsection 6.2.2.1. While the second one concerns the UIO for the system with measurement noises in subsection 6.2.2.2. The simulation results suggest that the proposed UIO works well for various reference signals (impulse, random, constant, and sine), several types of disturbances (impulse, random, constant, and sine), and with or without measurement noises.

6.2.2.1 Quadrotor Unknown Input Observer (UIO) without measurement noise

In this section, we simulate the Unknown Input Observer (UIO) for altitude/attitude of a mass-varying quadcopter under disturbances. Due to the variation of the mass, the moments of inertia with respect to the three axes $x$, $y$, and $z$ are also changing. The mass can be changed abruptly or gradually.

- The disturbances $d_\phi$, $d_\theta$, $d_\psi$, and $d_z$ to roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ of the quadcopter can be sinus, random, step, square wave, or constant.
- The reference signals for roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ can be of the form sinus, random, step, square wave, or constant.

The configuration of the LPV UIO for Altitude/Attitude of a mass-varying quadcopter is shown in Figure 6.34. For controlling the Altitude/Attitude of the quadrotor, the LPV $H_\infty$ state feedback controller designed in 5.6 is used. In this simulation, we do not consider the measurement noises, consequently, the measured values are directly the inputs to the LPV UIO block as shown in Figure 6.34.

For simplify, in the simulation, the derivatives of the outputs are calculated by generic differentiator. However, in the real cases, the time derivatives of the outputs can be corrupted by measurement noises. In this case, in order to get the derivatives of the outputs which are less sensitive to the measurement noises, sliding mode or algebraic differentiators can be applied.

![Figure 6.34: LPV $H_\infty$ UIO for mass-varying quadcopter configuration](image-url)
Scenario 5. In this simulation:

- No measurement noises are considered
- Simulation time is $30\,(s)$
- The mass gradually changes from $2\,(kg)$ to $1.12\,(kg)$ over a period of time from $5\,(s)$ to $25\,(s)$. Consequently, the moments of inertia also gradually change over a period of time from $5\,(s)$ to $25\,(s)$ as shown in Figure 6.35.
- The reference signals $\varphi_{\text{ref}}$, $\theta_{\text{ref}}$, $\psi_{\text{ref}}$, and $z_{\text{ref}}$ (Figure 6.38) are:
  - $\varphi_{\text{ref}}$ is a step signal at $2\,(s)$ from $0\,(deg)$ to $30\,(deg)$
  - $\theta_{\text{ref}}$ is a step signal at $4\,(s)$ from $0\,(deg)$ to $28\,(deg)$
  - $\psi_{\text{ref}}$ is a step signal at $6\,(s)$ from $0\,(deg)$ to $26\,(deg)$
  - $z_{\text{ref}}$ is a constant signal, $z_{\text{ref}} = 1\,(m)$
- The disturbances $d_{\varphi}$, $d_{\theta}$, $d_{\psi}$, and $d_{z}$ (Figure 6.36) are:
  - $d_{\varphi}$ is a sine wave signal of frequency $1\,(rad/s)$, amplitude is $1.1\,(Nm)$
  - $d_{\theta}$ is a sine wave signal of frequency $1\,(rad/s)$, amplitude is $1.3\,(Nm)$
  - $d_{\psi}$ is a sine wave signal of frequency $1\,(rad/s)$, amplitude is $1.5\,(Nm)$
  - $d_{z}$ is a random signal, maximum amplitude is $6\,(N)$ and , minimum amplitude is $-30\,(N)$

![Image of graph showing mass and moments of inertia over time](image-url)
Chapter 6. Simulation results

Figure 6.36: Scenario 5
UI and their estimation with LPV UIO for Alt/Att

Figure 6.37: Scenario 5
UI estimations errors with LPV UIO for Alt/Att

Figure 6.38: Scenario 5
Z, φ, θ, and ψ and estimations LPV UIO for Alt/Att

Figure 6.39: Scenario 5
Differences between (real and estimated) vs (real and measured) values LPV UIO for Alt/Att
6.2. Quadrotor Control simulations

The actual unknown inputs $d_z$, $d_\phi$, $d_\theta$, $d_\psi$ and their estimated values are shown in Figure 6.36 and Figure 6.37 shows the differences between actual unknown inputs and estimated unknown inputs. We can see that the estimated unknown inputs tend to actual unknown inputs in about 5 (s).

In Figure 6.38 are shown the desired, actual, and estimated value of $\phi$, $\psi$, and $z$. We can see that $\phi$, $\theta$, $\psi$, and $z$ track the reference signals well (as in Figure 6.38) even under disturbances and the changes of mass and moments of inertia. The response time for $\phi$, $\theta$, $\psi$, and $z$ are small.

The actual, and estimated value of $\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$, and $\dot{z}$ are shown in Figure 6.40, while Figure 6.41 shows the difference between the actual and estimated values of $\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$, and $\dot{z}$. □
Scenario 6. In this simulation:

- No measurement noise is considered
- Simulation time is 30(s)
- The mass abruptly changes at 5(s) from 2(kg) to 1.65(kg), at 10(s) from 1.65(kg) to 1.3(kg), at 15(s) from 1.3(kg) to 1.18(kg), and at 25(s) from 1.18(kg) to 1.12(kg). Consequently, the moments of inertia also change abruptly at 5(s), 10(s), 15(s), and 25(s) as shown in Figure 6.42.
- The reference signals $\varphi_{\text{ref}}, \theta_{\text{ref}}, \psi_{\text{ref}},$ and $z_{\text{ref}}$ (Figure 6.45) are:
  - $\varphi_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), maximum amplitude is $30$ (deg), minimum amplitude is $0$ (deg)
  - $\theta_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), maximum amplitude is $28$ (deg), minimum amplitude is $0$ (deg)
  - $\psi_{\text{ref}}$ is a square wave signal of frequency $1/6$ (Hz), maximum amplitude is $26$ (deg), minimum amplitude is $0$ (deg)
  - $z_{\text{ref}}$ is a constant signal, $z_{\text{ref}} = 1$ (m)
- The disturbances $d_{\varphi}, d_{\theta}, d_{\psi},$ and $d_{z}$ (Figure 6.43) are:
  - $d_{\varphi}$ is a random signal, maximum amplitude is $1.1$ (Nm) and minimum amplitude is $-1.1$ (Nm)
  - $d_{\theta}$ is a random signal, maximum amplitude is $1.3$ (Nm) and minimum amplitude is $-1.3$ (Nm)
  - $d_{\psi}$ is a random signal, maximum amplitude is $1.5$ (Nm) and minimum amplitude is $-1.5$ (Nm)
  - $d_{z}$ is a random signal, maximum amplitude is $6$ (N) and minimum amplitude is $-30$ (N)
6.2. Quadrotor Control simulations

Figure 6.43: Scenario 6
UI and their estimation with LPV UIO for Alt/Att

Figure 6.44: Scenario 6
UI estimations errors with LPV UIO for Alt/Att

Figure 6.45: Scenario 6
$Z$, $\phi$, $\theta$, and $\psi$ and estimations LPV UIO for Alt/Att

Figure 6.46: Scenario 6
Differences between (real and estimated) vs (real and measured) values LPV UIO for Alt/Att
Chapter 6. Simulation results

The actual unknown inputs \( d_z, d_\phi, d_\theta, d_\psi \) and their estimated values are shown in Figure 6.43 and Figure 6.44 shows the differences between actual unknown inputs and estimated unknown inputs. We can see that the estimated unknown inputs tend to actual unknown inputs in about 5 (s).

In Figure 6.45 are shown the desired, actual, and estimated value of \( \varphi, \theta, \psi, \) and \( z \). We can see that \( \varphi, \theta, \psi, \) and \( z \) track the reference signals well (as in Figure 6.45) even under disturbances and the changes of mass and moments of inertia. The response time for \( \varphi, \theta, \psi, \) and \( z \) are small.

The actual, and estimated value of \( \dot{\varphi}, \dot{\theta}, \dot{\psi}, \) and \( \dot{z} \) shown in Figure 6.47, while Figure 6.48 shows the difference between the actual and estimated values of \( \dot{\varphi}, \dot{\theta}, \dot{\psi}, \) and \( \dot{z} \).
6.2.2 Quadrotor Unknown Input Observer (UIO) with measurement noise

In this section, we simulate the Unknown Input Observer (UIO) for altitude/attitude of a mass-varying quadcopter under disturbances. Due to the variation of the mass, the moments of inertia with respect to the three axes $x$, $y$, and $z$ are also changing. The mass can be changed abruptly or gradually.

- The disturbances $d_\phi$, $d_\theta$, $d_\psi$, and $d_z$ to roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ of the quadcopter can be sinus, random, step, square wave, or constant.
- The reference signals for roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ can be of the form sinus, random, step, square wave, or constant.

The configuration of the LPV UIO for Altitude/Attitude of a mass-varying quadcopter is shown in Figure 6.49. For controlling the Altitude/Attitude of the quadrotor, the LPV $H_\infty$ state feedback controller designed in 5.6 is used. In this simulation, we consider the measurement noises. The outputs of the quadcopter are measured by the Measurement block. The white noises are added to the outputs of the quadcopter here (in Figure 6.49), then the noisy outputs of the quadcopter (the outputs of the Measurement block) are the inputs to the LPV UIO block.

![Diagram of Quadcopter Control Simulations](image)

Figure 6.49: LPV $H_\infty$ UIO for mass-varying quadcopter configuration
Scenario 7. In this simulation:

- Measurement noises (random white noises) are considered

- Simulation time is $30\,\text{s}$

- The mass abruptly changes at $5\,\text{s}$ from $2\,\text{kg}$ to $1.65\,\text{kg}$, at $10\,\text{s}$ from $1.65\,\text{kg}$ to $1.3\,\text{kg}$, at $15\,\text{s}$ from $1.3\,\text{kg}$ to $1.18\,\text{kg}$, and at $25\,\text{s}$ from $1.18\,\text{kg}$ to $1.12\,\text{kg}$. Consequently, the moments of inertia also change abruptly at $5\,\text{s}$, $10\,\text{s}$, $15\,\text{s}$, $25\,\text{s}$ as shown in Figure 6.50.

- The reference signals $\varphi_{\text{ref}}$, $\theta_{\text{ref}}$, $\psi_{\text{ref}}$, and $z_{\text{ref}}$ (Figure 6.53) are:
  - $\varphi_{\text{ref}}$ is a random signal, maximum amplitude is $22\,\text{deg}$, minimum amplitude is $-40\,\text{deg}$
  - $\theta_{\text{ref}}$ is a random signal, maximum amplitude is $30\,\text{deg}$, minimum amplitude is $-22\,\text{deg}$
  - $\psi_{\text{ref}}$ is a random signal, maximum amplitude is $48\,\text{deg}$, minimum amplitude is $-48\,\text{deg}$
  - $z_{\text{ref}}$ is a square wave signal of frequency $\frac{1}{6}\,\text{Hz}$, maximum amplitude is $1.5\,\text{m}$, minimum amplitude is $1\,\text{m}$

- The disturbances $d_\varphi$, $d_\theta$, $d_\psi$, and $d_z$ (Figure 6.51) are:
  - $d_\varphi$ is a sinus signal of frequency $\frac{1}{6}\,\text{Hz}$, maximum amplitude is $1.1\,\text{Nm}$ and minimum amplitude is $-1.1\,\text{Nm}$
  - $d_\theta$ is a sinus signal, maximum amplitude is $1.3\,\text{Nm}$ and minimum amplitude is $-1.3\,\text{Nm}$
  - $d_\psi$ is a sinus signal, maximum amplitude is $1.5\,\text{Nm}$ and minimum amplitude is $-1.5\,\text{Nm}$
  - $d_z$ is a square wave signal of frequency $\frac{1}{4}\,\text{Hz}$, maximum amplitude is $6\,\text{N}$ and minimum amplitude is $-40\,\text{N}$
6.2. Quadrotor Control simulations

Figure 6.51: Scenario 7
UI and their estimation with LPV UIO for Alt/Att

Figure 6.52: Scenario 7
UI estimations errors with LPV UIO for Alt/Att

Figure 6.53: Scenario 7
Z, φ, θ, and ψ and estimations LPV UIO for Alt/Att

Figure 6.54: Scenario 7
Differences between (real and estimated) vs (real and measured) values LPV UIO for Alt/Att
Chapter 6. Simulation results

\[ \dot{Z}, \dot{\phi}, \dot{\theta}, \text{and} \dot{\psi} \text{ and estimations LPV UIO for Alt/Att} \]

The actual unknown inputs \( d_z, d_\phi, d_\theta, \text{and} d_\psi \) and their estimated values are shown in Figure 6.51 and Figure 6.52 shows the differences between actual unknown inputs and estimated unknown inputs. We can see that the estimated unknown inputs tend to actual unknown inputs in about 5 (s).

In Figure 6.53 are shown the desired, actual, measured, and estimated value of \( \varphi, \theta, \psi, \text{and} z \). We can see that \( \varphi, \theta, \psi, \text{and} z \) track the reference signals well (as in Figure 6.53) even under disturbances and the abrupt changes of mass and moments of inertia. The response time for \( \varphi, \theta, \psi, \text{and} z \) are small.

The Figure 6.54 shows the differences between the real and estimated values, and between real and measured values of \( \dot{\varphi}, \dot{\theta}, \dot{\psi}, \text{and} \dot{z} \). These errors signals are really small compared to the actual values. We can see that, even under disturbances, the abrupt changes of mass and moments of inertia, and the measurement noises, the estimated values still track the actual values of \( \varphi, \theta, \psi, \text{and} z \) well.

The actual, and estimated value of \( \dot{\varphi}, \dot{\theta}, \dot{\psi}, \text{and} \dot{z} \) are showed in Figure 6.55, while Figure 6.56 shows the difference between the actual and estimated, and between the actual and measured values of \( \dot{\varphi}, \dot{\theta}, \dot{\psi}, \text{and} \dot{z} \). We can see that, even under disturbances, the changes of mass and moments of inertia, and the measurement noises, the estimated values still track the actual values of \( \varphi, \theta, \psi, \text{and} z \) well.

Some simulations has been conducted when the outputs of the quadcopter are disturbed by the same random white noise signals as given in 6.53 and 6.54, if the UIO is not applied, the control is lost.
Scenario 8. In this simulation:

- Measurement noises (random white noises) are considered
- Simulation time is 30(s)
- The mass gradually changes from 2(kg) to 1.12(kg) over a period of time from 5(s) to 25(s). Consequently, the moments of inertia also gradually change over a period of time from 5(s) to 25(s) as shown in Figure 6.57.
- The reference signals $\varphi_{ref}$, $\theta_{ref}$, $\psi_{ref}$, and $z_{ref}$ (Figure 6.60) are:
  - $\varphi_{ref}$ is a step signal at 2(s) from 0(deg) to 30(deg)
  - $\theta_{ref}$ is a step signal at 4(s) from 0(deg) to 28(deg)
  - $\psi_{ref}$ is a step signal at 6(s) from 0(deg) to 26(deg)
  - $z_{ref}$ is a square wave signal of frequency $1/6$ (Hz), maximum amplitude is 1.5(m), minimum amplitude is 1(m)
- The disturbances $d_{\varphi}$, $d_{\theta}$, $d_{\psi}$, and $d_{z}$ (Figure 6.58) are:
  - $d_{\varphi}$ is a random signal, maximum amplitude is 1.1(Nm) and minimum amplitude is $-1.1$ (Nm)
  - $d_{\theta}$ is a random signal, maximum amplitude is 1.3(Nm) and minimum amplitude is $-1.3$ (Nm)
  - $d_{\psi}$ is a random signal, maximum amplitude is 1.5(Nm) and minimum amplitude is $-1.5$ (Nm)
  - $d_{z}$ is a random signal, maximum amplitude is 6(N) and minimum amplitude is $-30$ (N)

![Figure 6.57: Scenario 8](image)
Chapter 6. Simulation results

Figure 6.58: Scenario 8
UIO Moments estimations
LPV UIO for Alt/Att

Figure 6.59: Scenario 8
UIO Moments estimations errors
LPV UIO for Alt/Att

Figure 6.60: Scenario 8
Z, φ, θ, and ψ and estimations
LPV UIO for Alt/Att

Figure 6.61: Scenario 8
Differences between (real and estimated) vs (real and measured) values
LPV UIO for Alt/Att
6.2. Quadrotor Control simulations

The actual unknown inputs $d_z$, $d_\phi$, $d_\theta$, and $d_\psi$ and their estimated values are shown in Figure 6.58 and Figure 6.59 shows the differences between actual unknown inputs and estimated unknown inputs. We can see that the estimated unknown inputs tend to actual unknown inputs in about 5 (s).

In Figure 6.60 are shown the desired, actual, measured, and estimated value of $\phi$, $\theta$, $\psi$, and $z$. We can see that $\phi$, $\theta$, $\psi$, and $z$ track the reference signals well (as in Figure 6.60) even under disturbances and the gradual changes of mass and moments of inertia. The response time for $\phi$, $\theta$, $\psi$, and $z$ are small.

The Figure 6.61 shows the differences between the real and estimated values, and between real and measured values of $\phi$, $\theta$, $\psi$, and $z$. We can see that, even under disturbances, the gradual changes of mass and moments of inertia, and the measurement noises, the estimated values still track the actual values of $\phi$, $\theta$, $\psi$, and $z$ well.

The actual, and estimated value of $\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$, and $\dot{z}$ are shown in Figure 6.62, while Figure 6.63 show the difference between the actual and estimated, and between the actual and measured values of $\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$, and $\dot{z}$. We can see that, even under disturbances, the changes of mass and moments of inertia, and the measurement noises, the estimated values still track the actual values of $\phi$, $\theta$, $\psi$, and $z$ well.

Some simulations has been conducted when the outputs of the quadcopter are disturbed by the same random white noise signals as given in 6.60 and 6.61 if the UIO is not applied, the control is lost.
6.2.3 Quadrotor path following

In this section, we simulate the full control for a mass-varying quadcopter under disturbances to follow predefined trajectory. Due to the variation of the mass, the moments of inertia with respect to the three axes $x$, $y$, and $z$ are also changing. The mass can be changed abruptly or gradually.

- The disturbances $d_\phi$, $d_\theta$, $d_\psi$, and $d_z$ to roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ of the quadcopter can be of the form sinus, random, step, square wave, or constant.

- The reference signals for roll $\phi$, pitch $\theta$, yaw $\psi$, and altitude $z$ can be of the form sinus, random, step, square wave, or constant.

The configuration of the full control for a mass-varying quadcopter is shown in Figure 6.64.
Scenario 9. In this simulation:

- No measurement noise is considered
- Simulation time is $90\,(s)$
- The mass of the quadcopter changes in the two manners:
  - The mass gradually changes from $2.0\,(kg)$ to $1.12\,(kg)$ over a period of time from $10\,(s)$ to $85\,(s)$. Consequently, the moments of inertia also gradually change over a period of time from $10\,(s)$ to $85\,(s)$ as shown in the first two sub-figures of Figure 6.65.
  - The mass abruptly changes at $10\,(s)$ from $2.0\,(kg)$ to $1.824\,(kg)$, at $20\,(s)$ from $1.824\,(kg)$ to $1.736\,(kg)$, at $30\,(s)$ from $1.736\,(kg)$ to $1.56\,(kg)$, at $40\,(s)$ from $1.56\,(kg)$ to $1.472\,(kg)$, at $50\,(s)$ from $1.472\,(kg)$ to $1.384\,(kg)$, at $60\,(s)$ from $1.384\,(kg)$ to $1.296\,(kg)$, at $70\,(s)$ from $1.296\,(kg)$ to $1.208\,(kg)$, and at $85\,(s)$ from $1.208\,(kg)$ to $1.12\,(kg)$. Consequently, the moments of inertia also change abruptly at $10\,(s)$, $20\,(s)$, $30\,(s)$, $40\,(s)$, $50\,(s)$, $60\,(s)$, $70\,(s)$, $85\,(s)$ as shown in the last two sub-figures of Figure 6.65.
- The quadrotor must follow a square trajectory as follows: Quadrotor moves from $(0,0,0)$ to $(0,0,2)$ over the interval of time $[0\,(s);5\,(s)]$, moves from $(0,0,2)$ to $(10,0,2)$ over the interval of time $[10\,(s);25\,(s)]$, moves from $(10,0,2)$ to $(10,10,2)$ over the interval of time $[25\,(s);45\,(s)]$, moves from $(10,10,2)$ to $(0,10,2)$ over the interval of time $[45\,(s);65\,(s)]$, moves from $(0,10,2)$ to $(0,0,2)$ over the interval of time $[65\,(s);85\,(s)]$, moves from $(0,0,2)$ to $(0,0,0)$ over the interval of time $[85\,(s);90\,(s)]$ as in Figure 6.70. Therefore, reference signals $x_{ref}$, $y_{ref}$, $z_{ref}$, and $\psi_{ref}$ are:
  - $x_{ref}$ keeps at $0\,(m)$ over the interval of time $[0\,(s);5\,(s)]$, changes from $0\,(m)$ to $10\,(m)$ over the interval of time $[5\,(s);25\,(s)]$, keeps at $10\,(m)$ over the interval of time $[25\,(s);45\,(s)]$, changes from $10\,(m)$ to $0\,(m)$ over the interval of time $[45\,(s);65\,(s)]$, keeps at $0\,(m)$ over the interval of time $[65\,(s);90\,(s)]$.
  - $y_{ref}$ keeps at $0\,(m)$ over the interval of time $[0\,(s);25\,(s)]$, changes from $0\,(m)$ to $10\,(m)$ over the interval of time $[25\,(s);45\,(s)]$, keeps at $10\,(m)$ over the interval of time $[45\,(s);65\,(s)]$, changes from $10\,(m)$ to $0\,(m)$ over the interval of time $[65\,(s);85\,(s)]$, keeps at $0\,(m)$ over the interval of time $[85\,(s);90\,(s)]$.
  - $z_{ref}$ changes from $0\,(m)$ to $2\,(m)$ over the interval of time $[0\,(s);5\,(s)]$, keeps at $2\,(m)$ over the interval of time $[5\,(s);85\,(s)]$, and changes from $2\,(m)$ to $0\,(m)$ over the interval of time $[85\,(s);90\,(s)]$.
  - $\psi_{ref} = 0\,(deg)$
- The disturbances $d_x$, $d_y$, and $d_z$ are $Wind_X$, $Wind_Y$, and $Wind_Z$ in (the first sub-figure of Figure 6.66) are:
  - $Wind_X$ is a square wave signal of frequency $1/9\,(Hz)$, maximum amplitude is $5.1\,(m/s)$, minimum amplitude is $0\,(m/s)$
  - $Wind_Y$ is a step signal at $5\,(s)$ from $0\,(m/s)$ to $4.8\,(m/s)$
WindZ is a square wave signal of frequency $1/10$ (Hz), maximum amplitude is 1.5 (m/s), minimum amplitude is 0 (m/s).

The results in Figure 6.66, 6.69, and 6.70 show that the quadcopter follows the reference trajectory well even under the disturbances. The Figure 6.68 shows the errors of the outputs and reference signals. We can see that, for x and y, the maximum values of the errors are less than 0.15m. This errors happen when the disturbances are applied.
6.2. Quadrotor Control simulations

Figure 6.67 show the inputs to the quadcopter $U_1, U_2, U_3,$ and $U_4$.

![Diagram showing inputs to the quadcopter](image)

**Figure 6.69:** Scenario 9

*X and Y in 2D Quadrotor path following*

**Figure 6.70:** Scenario 9

*X, Y, and Z in 3D Quadrotor path following*

![Diagram showing 3D path following](image)

**Figure 6.71:** Scenario 9

*X, Y, and Z vs time Quadrotor path following*

![Diagram showing time vs position](image)

The results in Figure 6.71 show that the mass variations (abrupt or gradual) do not effect to the ability of path following of the quadcopter. The quadcopter follows the reference trajectory even under the different types of disturbances and variations of the mass and moments of inertia.
Scenario 10. In this simulation:

- No measurement noise is considered
- Simulation time is 90(s)
- The mass of the quadcopter changes in the two manners:
  - The mass gradually changes from 2.0(kg) to 1.12(kg) over a period of time from 10(s) to 80(s). Consequently, the moments of inertia also gradually change over a period of time from 10(s) to 80(s) as shown in the first two sub-figures of Figure 6.72.
  - The mass abruptly changes at 10(s) from 2.0(kg) to 1.648(kg), at 30(s) from 1.648(kg) to 1.384(kg), at 50(s) from 1.384(kg) to 1.164(kg), and at 80(s) from 1.164(kg) to 1.12(kg). Consequently, the moments of inertia also change abruptly at 10(s), 30(s), 50(s), 80(s) as shown in the last two sub-figures of Figure 6.72.

- The quadrotor must follow a square trajectory as follows: Quadrotor moves from (0,0,0) to (0,0,2) over the interval of time [0(s);5(s)], moves from (0,0,2) to (10,0,2) over the interval of time [10(s);25(s)], moves from (10,0,2) to (10,10,2) over the interval of time [25(s);40(s)], moves from (10,10,2) to (0,10,2) over the interval of time [45(s);65(s)], moves from (0,10,2) to (0,0,2) over the interval of time [65(s);85(s)], moves from (0,0,2) to (0,0,0) over the interval of time [85(s);90(s)] as in Figure 6.77. Therefore, reference signals \( x_{ref}, y_{ref}, z_{ref}, \) and \( \psi_{ref} \) are:
  - \( x_{ref} \) keeps at 0(m) over the interval of time [0(s);5(s)], changes from 0(m) to 10(m) over the interval of time [5(s);25(s)], keeps at 10(m) over the interval of time [25(s);45(s)], changes from 10(m) to 0(m) over the interval of time [45(s);65(s)], keeps at 0(m) over the interval of time [65(s);90(s)].
  - \( y_{ref} \) keeps at 0(m) over the interval of time [0(s);25(s)], changes from 0(m) to 10(m) over the interval of time [25(s);45(s)], keeps at 10(m) over the interval of time [45(s);65(s)], changes from 10(m) to 0(m) over the interval of time [65(s);85(s)], keeps at 0(m) over the interval of time [85(s);90(s)].
  - \( z_{ref} \) changes from 0(m) to 2(m) over the interval of time [0(s);5(s)], keeps at 2(m) over the interval of time [5(s);85(s)], and changes from 2(m) to 0(m) over the interval of time [85(s);90(s)].
  - \( \psi_{ref} = 0(\text{deg}) \)

- The disturbances \( d_x, d_y, \) and \( d_z \) are \( \text{Wind}_X, \text{Wind}_Y, \) and \( \text{Wind}_Z \) in (the first sub-figure of Figure 6.73) are:
  - \( \text{Wind}_X \) is a square wave signal of frequency 1/9(Hz), maximum amplitude is 5.1(m/s), minimum amplitude is 0(m/s)
  - \( \text{Wind}_Y \) is a sine signal of frequency 1/40(Hz), maximum amplitude is 4.9(m/s), minimum amplitude is \(-4.9\)(m/s)
  - \( \text{Wind}_Z \) is a step signal at 6(s) from 0(m/s) to 1.5(m/s)
6.2. Quadrotor Control simulations

The results in Figure 6.73, 6.76 and 6.77 show that the quadcopter follows the reference trajectory well even under the disturbances. The Figure 6.75 shows the errors of the outputs and reference signals. We can see that, for $x$ and $y$, the maximum values of the errors are less than 0.15m. This errors happen when the disturbances are applied.

Figure 6.74 show the inputs to the quadcopter $U_1$, $U_2$, $U_3$, and $U_4$. 

Figure 6.72: Scenario 10
Mass, $I_x$, $I_y$, and $I_z$
Quadrotor path following

Figure 6.73: Scenario 10
$x$, $y$, and $z$, their responses, and disturbances
Quadrotor path following

Figure 6.74: Scenario 10
$U_1$, $U_2$, $U_3$ and $U_4$
Quadrotor path following

Figure 6.75: Scenario 10
Errors on $X$, $Y$, $Z$ and $\psi$
Quadrotor path following
Chapter 6. Simulation results

The results in Figure 6.78 show that the methods of mass variation (abrupt or gradual) do not affect the ability of path following of the quadcopter. The quadcopter follows the reference trajectory even under the different type of disturbances and variations of the mass and moments of inertia.

The quadcopter tracks the reference signal well even at the vertices of the rectangle as in Figures 6.76 and 6.77.
Scenario 11. In this simulation:

- No measurement noise is considered
- Simulation time is 90\(\text{s}\)
- The mass of the quadcopter changes in the two manners:
  - The mass gradually changes from 2.0\(\text{kg}\) to 1.12\(\text{kg}\) over a period of time from 5\(\text{s}\) to 80\(\text{s}\). Consequently, the moments of inertia also gradually change over a period of time from 5\(\text{s}\) to 80\(\text{s}\) as shown in the first two sub-figures of Figure 6.79.
  - The mass abruptly changes at 5\(\text{s}\) from 2.0\(\text{kg}\) to 1.824\(\text{kg}\), at 10\(\text{s}\) from 1.824\(\text{kg}\) to 1.648\(\text{kg}\), at 20\(\text{s}\) from 1.648\(\text{kg}\) to 1.560\(\text{kg}\), at 40\(\text{s}\) from 1.560\(\text{kg}\) to 1.472\(\text{kg}\), at 55\(\text{s}\) from 1.472\(\text{kg}\) to 1.164\(\text{kg}\), and at 80\(\text{s}\) from 1.164\(\text{kg}\) to 1.12\(\text{kg}\). Consequently, the moments of inertia also change abruptly at 5\(\text{s}\), 10\(\text{s}\), 20\(\text{s}\), 40\(\text{s}\), 55\(\text{s}\), 80\(\text{s}\) as shown in the last two sub-figures of Figure 6.79.

- The quadrotor must follow a circle trajectory as follows: Quadrotor moves from (0,0,0) to (0,0,2) over the interval of time [0\(\text{s}\);5\(\text{s}\)], moves along the circle with radius 5\(\text{m}\) and center (0,-5,2) over the interval of time [5\(\text{s}\);85\(\text{s}\)], moves from (0,0,2) to (0,0,0) over the interval of time [85\(\text{s}\);90\(\text{s}\)] as in Figure 6.84. Therefore, reference signals \(x_{\text{ref}}, y_{\text{ref}}, z_{\text{ref}},\) and \(\psi_{\text{ref}}\) are:
  - \(x_{\text{ref}}\) keeps at 0\(\text{m}\) over the interval of time [0\(\text{s}\);5\(\text{s}\)], changes along sine trajectory \(5\sin\left((t-5)\frac{\pi}{40}\right)\) over the interval of time [5\(\text{s}\);85\(\text{s}\)], keeps at 0\(\text{m}\) over the interval of time [85\(\text{s}\);90\(\text{s}\)].
  - \(y_{\text{ref}}\) keeps at 0\(\text{m}\) over the interval of time [0\(\text{s}\);5\(\text{s}\)], changes along sine trajectory \(5\cos\left((t-5)\frac{\pi}{40}\right)-5\) over the interval of time [5\(\text{s}\);85\(\text{s}\)], keeps at 0\(\text{m}\) over the interval of time [85\(\text{s}\);90\(\text{s}\)].
  - \(z_{\text{ref}}\) changes from 0\(\text{m}\) to 2\(\text{m}\) over the interval of time [0\(\text{s}\);5\(\text{s}\)], keeps at 2\(\text{m}\) over the interval of time [5\(\text{s}\);85\(\text{s}\)], and changes from 2\(\text{m}\) to 0\(\text{m}\) over the interval of time [85\(\text{s}\);90\(\text{s}\)].
  - \(\psi_{\text{ref}}\) = 0\(\text{deg}\)

- The disturbances \(d_x, d_y,\) and \(d_z\) are \(\text{Wind}_X, \text{Wind}_Y,\) and \(\text{Wind}_Z\) in (the first sub-figure of Figure 6.84) are:
  - \(\text{Wind}_X\) is a sine signal of frequency 1/40\(\text{Hz}\), maximum amplitude is 5.1\(\text{m/s}\), minimum amplitude is -5.1\(\text{m/s}\)
  - \(\text{Wind}_Y\) is a constant signal 4.9\(\text{m/s}\)
  - \(\text{Wind}_Z\) is a impulse signal of frequency 1/10\(\text{Hz}\), maximum amplitude is 2.5\(\text{m/s}\), minimum amplitude is 0\(\text{m/s}\)
The results in Figure 6.80, 6.83 and 6.84 show that the quadcopter follows the reference trajectory well even under the disturbances. The Figure 6.82 shows the errors of the outputs and reference signals. We can see that, for \( x \) and \( y \), the maximum values of the errors are less than 0.15 m. This errors happen when the disturbances are applied.

Figure 6.81 shows the inputs to the quadcopter \( U_1, U_2, U_3 \) and \( U_4 \).
The results in Figure 6.85 show that the mass variations (abrupt or gradual) do not effect to the ability of path following of the quadcopter. The quadcopter follows the reference trajectory even under the different type of disturbances and variations of the mass and moments of inertia.
Scenario 12. In this simulation:

- No measurement noise is considered
- Simulation time is 90 (s)
- The mass of the quadcopter changes in the two manners:
  - The mass gradually changes from 2.0 (kg) to 1.12 (kg) over a period of time from 15 (s) to 80 (s). Consequently, the moments of inertia also gradually change over a period of time from 15 (s) to 80 (s) as shown in the first two sub-figures of Figure 6.86.
  - The mass abruptly changes at 15 (s) from 2.0 (kg) to 1.736 (kg), at 40 (s) from 1.736 (kg) to 1.472 (kg), and at 80 (s) from 1.472 (kg) to 1.12 (kg). Consequently, the moments of inertia also change abruptly at 15 (s), 40 (s), and 80 (s) as shown in the last two sub-figures of Figure 6.86.
- The quadrotor must follow a circle trajectory as follows: Quadrotor moves from (0, 0, 0) to (0, 0, 2) over the interval of time as shown in Figure 6.87. Therefore, reference signals $x_{\text{ref}}, y_{\text{ref}}, z_{\text{ref}},$ and $\psi_{\text{ref}}$ are:
  - $x_{\text{ref}}$ keeps at 0 (m) over the interval of time $[0 (s); 5 (s)]$, changes along sine trajectory $5 \sin\left((t - 5) \frac{\pi}{40}\right)$ over the interval of time $[5 (s); 85 (s)]$, keeps at 0 (m) over the interval of time $[85 (s); 90 (s)]$.
  - $y_{\text{ref}}$ keeps at 0 (m) over the interval of time $[0 (s); 5 (s)]$, changes along sine trajectory $5 \cos\left((t - 5) \frac{\pi}{40}\right) - 5$ over the interval of time $[5 (s); 85 (s)]$, keeps at 0 (m) over the interval of time $[85 (s); 90 (s)]$.
  - $z_{\text{ref}}$ changes from 0 (m) to 2 (m) over the interval of time $[0 (s); 5 (s)]$, keeps at 2 (m) over the interval of time $[5 (s); 85 (s)]$, and changes from 2 (m) to 0 (m) over the interval of time $[85 (s); 90 (s)]$.
  - $\psi_{\text{ref}} = 0$ (deg)
- The disturbances $d_x$, $d_y$, and $d_z$ are $\text{Wind}_X$, $\text{Wind}_Y$, and $\text{Wind}_Z$ in (the first sub-figure of Figure 6.87) are:
  - $\text{Wind}_X$ is a sine wave signal of frequency $1/40$ (Hz), maximum amplitude is 5.1 (m/s), minimum amplitude is -5.1 (m/s)
  - $\text{Wind}_Y$ is a sine wave signal of frequency $\pi/40$ (Hz), maximum amplitude is 4.9 (m/s), minimum amplitude is -4.9 (m/s)
  - $\text{Wind}_Z$ is a sine wave signal of frequency $\pi/40$ (Hz), maximum amplitude is 2.5 (m/s), minimum amplitude is -2.5 (m/s)
6.2. Quadrotor Control simulations

The results in Figure 6.87, 6.90 and 6.91 show that the quadcopter follows the reference trajectory well even under the disturbances. The Figure 6.89 shows the errors of the outputs and reference signals. We can see that, for $x$ and $y$, the maximum values of the errors are less than 0.1m. This errors happen when the disturbances are applied.

Figure 6.88 show the inputs to the quadcopter $U_1$, $U_2$, $U_3$, and $U_4$. 
Chapter 6. Simulation results

The results in Figure 6.92 show that the methods of mass variation (abrupt or gradual) do not affect the ability of path following of the quadcopter. The quadcopter follows the reference trajectory even under the different type of disturbances and variations of the mass and moments of inertia.

The quadcopter tracks the reference signal well even at the vertices of the rectangle as in Figures 6.90 and 6.91.
6.3 Conclusion

In this chapter, we have simulated different scenarios for both the complete coverage path planning and control of mass-varying quadrotor.

For the complete coverage path planning, the proposed algorithm generates the best trajectory for quadrotor to capture the pictures of the whole agriculture areas. Based on the gathered pictures, the infected crop areas are detected. The second task of complete coverage path planning is to generate the best trajectory for the quadrotor to spray pesticide to all the infected areas. The simulations show the ability of the proposed algorithm to generate the trajectory not only to cover the whole predefined areas but also with the minimum trajectory while avoiding obstacles.

For the control part, several control simulations for LPV $H_\infty$ state feedback controller, static output feedback controller, dynamic output feedback controller have been conducted. The simulation results show the ability of good reference tracking (several types of references are considered such as sine, step, square wave, random) under the existence of disturbances (several types of disturbances are considered such as sine, step, square wave, random) and changes of dynamic parameters of quadrotor (mass and moments of inertia). We also conducted simulations for LPV UIO. The results show that the proposed LPV UIO can well estimate the unknown disturbances and the states of the system.
7

General conclusion and perspectives

7.1 Conclusions

In this research work, we have proposed some new algorithms for Coverage Path Planning (CPP) and control of quadcopter for Precision Agriculture (PA), such as pest-ridden area detection and spraying insecticides. We started the manuscript by an introduction to the importance and application of robotics in precision agriculture to increase crop yields. Then, we emphasized our goals and main contributions and we look at the drones, their classification, their applications. Based on the above analysis, the quadrotor has been selected as the research object in the content of this thesis. Next, we studied CPP algorithms and control laws that have been applied to the quadrotors.

In the first part, we present a new complete CPP algorithm by proposing a new Cellular Decomposition (CD) which is based on a generalization of a Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a decrease in the number of cells after decomposition. Genetic Algorithm (GA) and Travelling Salesman Problem (TSP) algorithm are then applied to obtain the shortest path for complete coverage. Next, from the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. Then an algorithm is proposed for generating the best path for a UAV to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas, and pests-ridden areas.

In the second part, we study the design of a robust control law that allows the UAV to track the predefined trajectory for a dynamic model-changing helicopter due to the changes of dynamic coefficients such as the mass and moments of inertia. Therefore, robust observer and control law are required to adopt the changes in dynamic parameters as well as the impact of external forces. The proposed approach is to explore the modeling techniques, planning, and control by the Takagi-Sugeno type technique. To have easily implantable algorithms and adaptable to changes in parameters and conditions of use, we favor the synthesis of Linear Parameter Varying (LPV) Unknown Input Observer (UIO), LPV quadratic state feedback, robust state feedback, and static output feedback controllers. The observers and controllers are designed by solving a set of Linear Matrix Inequality (LMI) obtained from the Bounded Real Lemma and Linear Matrix Inequality (LMI) conditions.
In summary, besides the generic dynamic model that we have proposed for multirotors that may fly under wind gust, the performed work contains the following achievements:

- **Coverage path planning**

  1. Firstly, we propose a new approach for cellular decomposition. Based on the critical points as in [45] and [225], the extension of this approach is that the critical points have been categorized to several groups, and the cells have been created from these groups. This extension leads to a decrease of the number of cells after decomposition. The results show that this new cellular decomposition works well even with several concave obstacles inside the environment.

  2. Secondly, we have proposed a method for maximizing the percentage of coverage and we have given some comments for the trade-off between the percentage of coverage and the number of way-points for the UAV. The percentage of coverage is up to 97.9%.

  3. Finally, by using [GA] with some modification on the swap, flip and slide operations and the [TSP] with some additional constraints, the shortest path for changing the cells has been developed. This algorithm guarantees that the solution always exists and the time for calculation is decreasing.

  4. For the second task, we have proposed a method for generating a trajectory which allows the [UAV] to put the medicine to the entire pest-ridden area of an agricultural area. First, the pest-ridden areas have been divided into several smaller areas (clusters) by using clustering technique. After that, each cluster is divided again into several obstacle-free convex polygons. Then the shortest Boustrophedon trajectory is created in each obstacle-free convex polygon. Finally, the shortest trajectory for changing between obstacle-free convex polygons is generated for the final trajectory.

- **Control**

  1. If the states of [UAV] can be measured of estimated, we developed an [LPV] $H_\infty$ state feedback controller for mass-varying quadrotor. This controller is robustly stable under the disturbances.

  2. When the states might not be available, the dynamic and static [LPV] controllers have been proposed for mass-varying quadrotor.

  3. In order to overcome unmeasured states, we proposed also the Linear Parameter Varying [LPV] Unknown Input Observer [UIO] for mass-varying quadrotor.

### 7.2 Perspectives

In the following, we list some challenges that one may highlight in the future.

- **Coverage path planning issues**

  1. In the research content of this thesis, the issue of energy optimization has not been considered. Therefore, the energy optimization problem should be considered.
Furthermore, the UAVs must be aware of the remaining energy level and be able to return to the given locations before running out of energy.

2. For large agricultural areas, one UAV cannot completely perform the CPP task. Hence the expansion of the CPP problem for a team of UAVs is necessary. In addition, even if one quadrotor is totally damaged or in trouble, others may take over the coverage subtask.

3. The proposed coverage path-planning algorithm considers only off-line in 2D work-space with static obstacles. The 3D dynamic environment could be an interesting extension for the CPP.

4. The trajectory generated by the proposed CPP does not consider the dynamic constraints of the UAV. For example, the UAV is not able to make a sharp turn. We have to consider also constraints on the limit speed and acceleration of the UAV for the CPP problem.

5. Several extensions from this section are possible. One might consider recalculating the trajectory under the windy condition of the environment or trajectory generation for a team of UAV. Field tests are also subject of future work. The continuation of this work is also to add the UAV equations of motion as constraints on the path. Then the efficiency of the algorithm will be improved to be real-time usable.

- Control issues

1. The mass and moments of inertia of the quadrotor in the research content of this thesis are calculated according to the amount of pesticide sprayed over time. An extension of this could be the on-line estimation of the quadrotor mass and moments of inertia according to parameters measured from sensors such as accelerometer, gyroscope, etc

2. The control laws need to be simulated on Robot Operating System (ROS), developed on embedded computers, and applied to the real platform quadrotors.
This section presents some preliminaries about gain-scheduling, with particular emphasis on Linear Parameter Varying (LPV) systems. Then, we also review analysis and design of LPV control systems using the quadratic framework and discussing several possible specifications, like stability, $\mathcal{D}$-stability (pole clustering in a subset of the complex plane), $H_\infty/H_2$ performance, and finite-time stability/boundedness.

### A.0.1 Linear Parameter Varying (LPV) system

**Definition A.1.** Linear Parameter Varying (LPV) systems are linear dynamical systems whose mathematical description depends on parameters that change values over time. The system matrices are fixed functions of some varying parameters $\rho \in \mathbb{R}^n$, assumed to be unknown a priori but measured or estimated in real-time. LPV systems are described by equations of the form as follows:

\[
\begin{align*}
\dot{x}(\tau) &= A(\rho(\tau)) x(\tau) + B(\rho(\tau)) u(\tau), \quad \tau \geq 0 \\
y(\tau) &= C(\rho(\tau)) x(\tau) + D(\rho(\tau)) u(\tau) \\
x(0) &= x_0
\end{align*}
\]

(A.1)

where

- The notation $\dot{x}(\tau)$ stands for $x'(\tau)$ for continuous systems and for $x(k+1)$ for discrete systems.
- $x \in \mathbb{R}^{n_x}$, $u \in \mathbb{R}^{n_u}$, and $y \in \mathbb{R}^{n_y}$ are the state, input, and output vectors respectively. The system matrices are $A(\rho(\tau)) \in \mathbb{R}^{n_x \times n_x}$, $B(\rho(\tau)) \in \mathbb{R}^{n_x \times n_u}$, $C(\rho(\tau)) \in \mathbb{R}^{n_y \times n_x}$, and $D(\rho(\tau)) \in \mathbb{R}^{n_y \times n_u}$.

\[
\]

**Remark A.1.** The equation (A.1) describes both Continuous Time Linear Parameter Varying (CT LPV) and Discrete Time Linear Parameter Varying (DT LPV).

- For CT LPV $\tau = t$, and (A.1) becomes

\[
\begin{align*}
\dot{x}(t) &= A(\rho(t)) x(t) + B(\rho(t)) u(t), \quad t \geq 0 \\
y(t) &= C(\rho(t)) x(t) + D(\rho(t)) u(t) \\
x(0) &= x_0
\end{align*}
\]

(A.2)
• For $\mathcal{DTLPV}$, $\tau = k$, and (A.1) becomes
\[
\begin{align*}
    x(k+1) &= A(\rho(k))x(k) + B(\rho(k))u(k), \quad k \geq 0 \\
    y(k) &= C(\rho(k))x(k) + D(\rho(k))u(k) \\
    x(0) &= x_0
\end{align*}
\]  

\[\square\]

**Definition A.2.** (Generic Parameter Dependent system [46]) The Generic Parameter Dependent system is the system in the form
\[
\begin{align*}
    \sigma \cdot x(\tau) &= A(\rho(\tau))x(\tau) + B_u(\rho(\tau))u(t) + B_w(\rho(\tau))w(t) \\
    z(\tau) &= C_z(\rho(\tau))x(\tau) + D_{zu}(\rho(\tau))u(t) + D_{zw}(\rho(\tau))w(t) \\
    y(\tau) &= C_y(\rho(\tau))x(\tau) + D_{yw}(\rho(\tau))w(t) \\
    x(0) &= x_0
\end{align*}
\]
where $x \in \mathbb{R}^{nx}$, $u \in \mathbb{R}^{nu}$, $y \in \mathbb{R}^{ny}$, $w \in \mathbb{R}^{nw}$, and $z \in \mathbb{R}^{nz}$ are the state, input, measured output, exogenous input, and controlled output vectors respectively. The system matrices are $A(\rho(\tau)) \in \mathbb{R}^{nx \times nx}$, $B_u(\rho(\tau)) \in \mathbb{R}^{nx \times nu}$, $B_w(\rho(\tau)) \in \mathbb{R}^{nz \times nw}$, $C_z(\rho(\tau)) \in \mathbb{R}^{nz \times nx}$, $D_{zu}(\rho(\tau)) \in \mathbb{R}^{nz \times nu}$, $D_{zw}(\rho(\tau)) \in \mathbb{R}^{nz \times nw}$, $C_y(\rho(\tau)) \in \mathbb{R}^{ny \times nx}$, $D_{yu}(\rho(\tau)) \in \mathbb{R}^{ny \times nu}$, $D_{yw}(\rho(\tau)) \in \mathbb{R}^{ny \times nw}$.

\[\square\]

**Remark A.2.** The equation (A.4) describes both continuous time and discrete time generic parameter dependent system according to $\sigma$.

• For continuous time and generic parameter dependent system, $\tau = t$, and (A.4) becomes
\[
\begin{align*}
    \dot{x}(t) &= A(\rho(t))x(t) + B_u(\rho(t))u(t) + B_w(\rho(t))w(t) \\
    z(t) &= C_z(\rho(t))x(t) + D_{zu}(\rho(t))u(t) + D_{zw}(\rho(t))w(t) \\
    y(t) &= C_y(\rho(t))x(t) + D_{yw}(\rho(t))w(t)
\end{align*}
\]  

\[\square\]

• For discrete time generic parameter dependent system, $\tau = k$, and (A.4) becomes
\[
\begin{align*}
    x(k+1) &= A(\rho(k))x(k) + B_u(\rho(k))u(t) + B_w(\rho(k))w(t) \\
    z(k) &= C_z(\rho(k))x(k) + D_{zu}(\rho(k))u(t) + D_{zw}(\rho(k))w(t) \\
    y(k) &= C_y(\rho(k))x(k) + D_{yw}(\rho(k))u(t)
\end{align*}
\]  

\[\square\]

**Definition A.3.** The $N$-unit simplex, denoted by $\Lambda_N$, is defined as the set
\[
\Lambda_N := \left\{ \chi \in \mathbb{R}_+^N : \sum_{i=1}^N \chi_i = 1 \right\}
\]  

\[\square\]
Definition A.4. The LPV system in (A.1) is called polytopic if its state space system matrices can be represented as follows

\[
A(\rho(\tau)) = \sum_{i=1}^{N} \mu_i(\tau) A_i \\
B(\rho(\tau)) = \sum_{i=1}^{N} \mu_i(\tau) B_i \\
C(\rho(\tau)) = \sum_{i=1}^{N} \mu_i(\tau) C_i \\
D(\rho(\tau)) = \sum_{i=1}^{N} \mu_i(\tau) D_i
\]  

(A.8)

where \( A_i, B_i, C_i, D_i \) denote the so-called vertex systems, and \( \mu_i, i = 1, \ldots, N \) are the coefficients of the polytopic decomposition such that

\[
\sum_{i=1}^{N} \mu_i(\rho(\tau)) = 1, \quad \mu_i(\rho(\tau)) \geq 0, \quad \forall i = 1, \ldots, N, \quad \forall \rho \in \Theta
\]  

(A.10)

From definition A.4, the LPV polytopic system in (A.1) can be rewritten as

\[
\sigma \cdot x(\tau) = \sum_{i=1}^{N} \mu_i(\tau) [A_i x(\tau) + B_i u(\tau)] \\
y(\tau) = \sum_{i=1}^{N} \mu_i(\tau) [C_i x(\tau) + D_i u(\tau)]
\]  

(A.9)

Definition A.5. (Poles of an LPV system [82]) Given an autonomous LPV system

\[
\sigma \cdot x(\tau) = A(\rho(\tau)) x(\tau)
\]  

(A.11)

where the state vector \( x \in \mathbb{R}^{n_x} \), the varying parameter vector \( \rho(\tau) \in \Theta \subseteq \mathbb{R}^{n_{\rho}} \), and the system matrix \( A(\rho(\tau)) \in \mathbb{R}^{n_x \times n_x} \). The poles of (A.11) are the set of all the Linear Time Invariant (LTI) system obtained by freezing \( \rho(\tau) \) for all \( \rho \in \Theta \).}

Definition A.6. (\(D\)-stability of an LPV system) Given a subset \( \mathcal{D} \) of the complex plane. The autonomous LPV system (A.11) is called to be \( D \)-stable if all its poles lie in \( \mathcal{D} \).

Definition A.7. (LMI regions [43]) A subset \( \mathcal{D} \) of the complex plane is called a LMI region if there exist matrices \( \alpha = [\alpha_{kl}]_{k,l \in \{1, \ldots, m\}} \in S^{m \times m} \) and \( \beta = [\beta_{kl}]_{k,l \in \{1, \ldots, m\}} \in S^{m \times m} \) such that

\[
\mathcal{D} = \{ z \in C : f_{\mathcal{D}}(z) \prec 0 \}
\]  

(A.12)

where \( f_{\mathcal{D}} \) is the characteristic function

\[
f_{\mathcal{D}}(z) = \alpha + \beta z + \beta^T z^* = [\alpha_{kl} + \beta_{kl} z + \beta^T_{kl} z^*]_{k,l \in \{1, \ldots, m\}}
\]  

(A.13)

There are several typical LMI regions as follows:

- Left-hand semiplanes \( \text{Re}(z) < \lambda \)

\[
\alpha = -2\lambda \quad \beta = 1
\]
• **Right-hand semiplanes** \( \text{Re}(z) > \lambda \)
  \[
  \alpha = 2\lambda \quad \beta = -1
  \]

• **Disks of radius** \( r \) **and center** \((-c,0)\)
  \[
  \alpha = \begin{bmatrix} r & c \\ c & -r \end{bmatrix} \quad \beta = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}
  \]

• **Horizontal strips** \(-\omega \leq \text{Im}(z) \leq \omega\)
  \[
  \alpha = \begin{bmatrix} -2\omega & 0 \\ 0 & -2\omega \end{bmatrix} \quad \beta = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}
  \]

\[\square\]

**Definition A.8.** (\(H_\infty\) norm [78]) The \(H_\infty\) norm of a stable real-rational transfer matrix \(T(\sigma)\) of CT and DT systems are defined as

- **for CT system:**
  \[
  \|T(s)\|_\infty = \sup_{\omega \in \mathbb{R}} \sigma_{\text{max}}(T(j\omega))
  \] (A.14)

- **for DT system:**
  \[
  \|T(z)\|_\infty = \sup_{\omega \in [-\pi, \pi]} \sigma_{\text{max}}(T(e^{j\omega}))
  \] (A.15)

where \(\sigma_{\text{max}}(*)\) is the largest singular value of the matrix *.

\(H_\infty\)-norm is an important quantity for measuring robust stability, error in model order reduction. The \(H_\infty\)-norm can also be used to measuring the system input-output gain of finite energy signals. \[\square\]

**Definition A.9.** (\(H_\infty\) performance of an LPV system [202]) Given a LPV system defined as follows:

\[
\begin{align*}
\sigma \cdot x(t) &= A(\rho(t))x(t) + B(\rho(t)\omega(t)) \\
        z(t) &= C(\rho(t))x(t) + D(\rho(t)\omega(t))
\end{align*}
\] (A.16)

\(\gamma_\infty\) is called the \(H_\infty\) performance of the system (A.16) if \(\|T_{zw}(\sigma, \rho)\|_\infty < \gamma_\infty\) for all \(\rho \in \Theta\), where \(T_{zw}(\sigma, \rho)\) is the closed-loop transfer function from \(w(t)\) to \(z(t)\). \[\square\]

**Definition A.10.** (\(H_2\) norm [203]) Given a stable real-rational transfer matrix \(T(\sigma)\). The \(H_2\) norm of CT and DT \(T\) is defined as:

- **for CT system:**
  \[
  \|T(s)\|_2 = \sqrt{\frac{1}{2\pi} \int_{-\infty}^{\infty} \text{Tr} \left[ T(j\omega)^T T(j\omega) \right] d\omega}
  \] (A.17)

- **for DT system:**
  \[
  \|T(z)\|_2 = \sqrt{\frac{1}{2\pi} \int_{-\pi}^{\pi} \text{Tr} \left[ T(e^{j\omega})^T T(e^{j\omega}) \right] d\omega}
  \] (A.18)
where $\text{Tr}(\ast)$ is the trace of the matrix $\ast$.

**Definition A.11.** ($H_2$ performance of a LPV system [202]) Given a LPV system defined as follows:

$$
\sigma \cdot x(t) = A(\rho(t)) x(t) + B(\rho(t)) \omega(t) \\
z(t) = C(\rho(t)) x(t)
$$

(\text{A.19})

$\gamma_2$ is called the $H_2$ performance of the system (A.19) if

$$
\| T_{zw}(\sigma, \rho) \|_2 < \gamma_2 \text{ for all } \rho \in \Theta,
$$

where $T_{zw}(\sigma, \rho)$ is the closed-loop transfer function from $w(t)$ to $z(t)$.

Note that, the $H_2$ performance is really effective for handling stochastic aspects such as measurement noise and random disturbances.

**Theorem A.1.** (Quadratic stability of CT LPV systems [23][83]) The autonomous CT LPV system in (A.11) is quadratically stable

1. if there exists a positive definite matrix $P$ such that

$$
A(\rho)^T P + PA(\rho) \prec 0, \quad \forall \rho \in \Theta
$$

(A.20)

2. if there exists a positive definite matrix $Q$ such that

$$
QA(\rho)^T + A(\rho) Q \prec 0, \quad \forall \rho \in \Theta
$$

(A.21)

**Theorem A.2.** (Quadratic stability of DT LPV systems [118][73]) The autonomous DT LPV system in (A.11) is quadratically stable

1. if there exists a positive definite matrix $P$ such that

$$
A(\rho)^T P A(\rho) - P \prec 0, \quad \forall \rho \in \Theta
$$

(A.22)

2. if there exists a positive definite matrix $P$ such that

$$
\begin{bmatrix}
-P & PA(\rho) \\
A(\rho)^T P & -P
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
$$

(A.23)

3. if there exists a positive definite matrix $P$ such that

$$
\begin{bmatrix}
-Q & A(\rho) Q \\
QA(\rho)^T & -Q
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
$$

(A.24)

**Theorem A.3.** (Quadratic D-stability of LPV systems [160]) Given a LMI region $\mathcal{D}$ defined as in (A.12), the autonomous LPV system:

$$
\sigma \cdot x(t) = A(\rho) x(t)
$$

(A.25)

The system (A.25) is said to be quadratically $\mathcal{D}$-stable:
Appendix A. Preliminaries

1. if there exists $P > 0$ such that:
\[
\begin{bmatrix}
\alpha \otimes P + \beta \otimes PA + \beta^T \otimes A^T P \\
B(\rho)^T P \\
C(\rho)
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.26)

2. if there exists $Q > 0$ such that:
\[
\begin{bmatrix}
\alpha \otimes Q + \beta \otimes AQ + \beta^T \otimes QA^T \\
B(\rho)^T P \\
C(\rho)
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.27)

Theorem A.4. (Quadratic $H_\infty$ performance of CT LPV systems [43]) The CT LPV system has quadratic $H_\infty$ performance $\gamma_\infty$

1. if there exists $P > 0$ such that:
\[
\begin{bmatrix}
A(\rho)^T P + PA(\rho) & PB(\rho) & C(\rho)^T \\
B(\rho)^T P & -I & D(\rho)^T \\
C(\rho) & D(\rho) & -\gamma_\infty^2 I
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.28)

or equivalent to [15]
\[
\begin{bmatrix}
A(\rho)^T P + PA(\rho) & PB(\rho) & C(\rho)^T \\
B(\rho)^T P & -\gamma_\infty I & D(\rho)^T \\
C(\rho) & D(\rho) & -\gamma_\infty I
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.29)

2. if there exists $Q > 0$ such that:
\[
\begin{bmatrix}
A(\rho) Q + QA(\rho)^T & B(\rho) & QC(\rho)^T \\
B(\rho)^T & -I & D(\rho)^T \\
C(\rho) Q & D(\rho) & -\gamma_\infty^2 I
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.30)

or equivalent to [15]
\[
\begin{bmatrix}
A(\rho) Q + QA(\rho)^T & B(\rho) & QC(\rho)^T \\
B(\rho)^T & -I & D(\rho)^T \\
C(\rho) Q & D(\rho) & -\gamma_\infty I
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.31)

Theorem A.5. (Quadratic $H_\infty$ performance of DT LPV systems) The DT LPV system has quadratic $H_\infty$ performance $\gamma_\infty$

1. if there exists $P > 0$ such that:
\[
\begin{bmatrix}
P & PA(\rho) & PB(\rho) & 0 \\
A(\rho)^T P & 0 & C(\rho)^T \\
B(\rho)^T P & 0 & \gamma_\infty^2 I & D(\rho)^T \\
0 & C(\rho) & D(\rho) & I
\end{bmatrix} < 0, \quad \forall \rho \in \Theta
\] (A.32)
or equivalent to \[15\]
\[
\begin{bmatrix}
P & PA(\rho) & PB(\rho) & 0 \\
A(\rho)^{T}P & P & 0 & C(\rho)^{T} \\
B(\rho)^{T}P & 0 & \gamma_{\infty}I & D(\rho)^{T} \\
0 & C(\rho) & D(\rho) & \gamma_{\infty}I
\end{bmatrix} > 0, \ \forall \rho \in \Theta \quad (A.33)
\]

2. if there exists \( Q > 0 \) such that:
\[
\begin{bmatrix}
Q & A(\rho)Q & B(\rho) & 0 \\
QA(\rho)^{T} & Q & 0 & QC(\rho)^{T} \\
B(\rho)^{T} & 0 & \gamma_{\infty}^{2}I & D(\rho)^{T} \\
0 & C(\rho)Q & D(\rho) & I
\end{bmatrix} > 0, \ \forall \rho \in \Theta \quad (A.34)
\]

or equivalent to \[15\]
\[
\begin{bmatrix}
Q & A(\rho)Q & B(\rho) & 0 \\
QA(\rho)^{T} & Q & 0 & QC(\rho)^{T} \\
B(\rho)^{T} & 0 & \gamma_{\infty}I & D(\rho)^{T} \\
0 & C(\rho)Q & D(\rho) & \gamma_{\infty}I
\end{bmatrix} > 0, \ \forall \rho \in \Theta \quad (A.35)
\]

The problem with the conditions provided in Theorems A.1-A.5 is that they rely on the satisfaction of infinite number of constraints. This is really hard or even impossible for satisfaction. This difficulty can be overcome by considering the polytopic form \[46\] which allow to extract tractable conditions as in the following results.

**Theorem A.6. (Quadratic stability of polytopic CT LPV systems\[191\])**

Given an autonomous polytopic CT LPV system
\[
\dot{x}(t) = \sum_{i=1}^{N} \mu_{i}(\rho(t)) A_{i}x(t) \quad (A.36)
\]
where \( \mu_{i}, i = 1,...,N \) satisfies (A.10). The system (A.36) is said to be quadratically stable:

1. if there exists \( P > 0 \) such that:
\[
A_{i}^{T}P + PA_{i} < 0, \ \forall i = 1,...,N \quad (A.37)
\]

2. if there exists \( Q > 0 \) such that:
\[
QA_{i}^{T} + A_{i}Q < 0, \ \forall i = 1,...,N \quad (A.38)
\]

**Theorem A.7. (Quadratic stability of polytopic DT LPV systems\[191\])**

Given an autonomous polytopic DT LPV system
\[
x(k+1) = \sum_{i=1}^{N} \mu_{i}(\rho(k)) A_{i}x(k) \quad (A.39)
\]
where \( \mu_{i}, i = 1,...,N \) satisfies (A.10). The system (A.39) is said to be quadratically stable:
1. if there exists $P > 0$ such that:

$$
\begin{bmatrix}
-P & PA_i \\
-A_i^T P & -P
\end{bmatrix} < 0, \quad \forall i = 1, \ldots, N \tag{A.40}
$$

2. if there exists $Q > 0$ such that:

$$
\begin{bmatrix}
-Q & A_i Q \\
-Q A_i^T & -Q
\end{bmatrix} < 0, \quad \forall i = 1, \ldots, N \tag{A.41}
$$

Theorem A.8. (Quadratic D-stability of polytopic LPV systems[191]) Given an LMI region $D$ defined as in (A.13), the autonomous polytopic LPV system:

$$
\sigma \cdot x(t) = \sum_{i=1}^{N} \mu_i(\rho(t)) A_i x(t) \tag{A.42}
$$

where $\mu_i, i = 1, \ldots, N$ satisfies (A.10). The system (A.42) is said to be quadratically $D$-stable:

1. if there exists $P > 0$ such that:

$$
\alpha \otimes P + \beta \otimes PA_i + \beta^T \otimes A_i^T P = \left[ \alpha_{kl} P + \beta_{kl} PA_i + \beta_{kl} A_i^T P \right]_{k,l \in \{1, \ldots, m\}} < 0, \quad \forall i = 1, \ldots, N \tag{A.43}
$$

2. if there exists $Q > 0$ such that:

$$
\alpha \otimes Q + \beta \otimes A_i Q + \beta^T \otimes QA_i^T = \left[ \alpha_{kl} Q + \beta_{kl} A_i Q + \beta_{kl} QA_i^T \right]_{k,l \in \{1, \ldots, m\}} < 0, \quad \forall i = 1, \ldots, N \tag{A.44}
$$

Theorem A.9. (Quadratic $H\infty$ performance of polytopic CT LPV systems[191]) Given a CT LPV system defined as follows:

$$
\begin{align*}
\dot{x}(t) &= \sum_{i=1}^{N} \mu_i(\rho(t)) [A_i x(t) + B_i \omega(t)] \\
z(t) &= \sum_{i=1}^{N} \mu_i(\rho(t)) [C_i x(t) + D_i \omega(t)]
\end{align*} \tag{A.45}
$$

where $\mu_i, i = 1, \ldots, N$ satisfies (A.10). The system (A.45) has quadratic $H\infty$ performance $\gamma_{\infty}$:

1. if there exists $P > 0$ such that:

$$
\begin{bmatrix}
A_i^T P + PA_i & PB_i & C_i^T \\
B_i^T P & -I & D_i^T \\
C_i & D_i & -\gamma_{\infty}^2 I
\end{bmatrix} < 0, \quad \forall i = 1, \ldots, N \tag{A.46}
$$
2. if there exists $Q \succ 0$ such that:
\[
\begin{bmatrix}
A_i Q + QA_i^T & B_i & QC_i^T \\
B_i^T P & -I & D_i^T \\
C_i Q & D_i & -\gamma^2_i I
\end{bmatrix} \prec 0, \quad \forall i = 1, \ldots, N
\tag{A.47}
\]

\[\blacksquare\]

Theorem A.10. (Quadratic $H_\infty$ performance of polytopic $DT$ LPV systems) Given an $DT$ LPV system defined as follows:
\[
x(k+1) = \sum_{i=1}^{N} \mu_i(\rho(k))[A_i x(k) + B_i w(k)] \\
z(k) = \sum_{i=1}^{N} \mu_i(\rho(k))[C_i x(k) + D_i w(k)]
\tag{A.48}
\]
where $\mu_i, i = 1, \ldots, N$ satisfies (A.10). The system (A.48) has quadratic $H_\infty$ performance $\gamma_\infty$:

1. if there exists $P \succ 0$ such that:
\[
\begin{bmatrix}
P & PA_i & PB_i & 0 \\
A_i^T P & P & 0 & C_i^T \\
B_i^T P & 0 & I & D_i^T \\
0 & C_i & D_i & \gamma^2_i I
\end{bmatrix} \succ 0, \quad \forall \rho \in \Theta
\tag{A.49}
\]

2. if there exists $Q \succ 0$ such that:
\[
\begin{bmatrix}
Q & A_i Q & B_i & 0 \\
A_i^T Q & Q & 0 & QC_i^T \\
B_i^T Q & 0 & I & D_i^T \\
0 & C_i Q & D_i & \gamma^2_i I
\end{bmatrix} \succ 0, \quad \forall \rho \in \Theta
\tag{A.50}
\]

\[\blacksquare\]

Theorem A.11. (Quadratic Stabilization of $CT$ LPV systems - State feedback) Consider $CT$ LPV system given in the first equation of (A.1). This $CT$ LPV system is quadratically stable by a state feedback control law given by
\[
u(t) = K(\rho(t)) x(t)
\tag{A.51}
\]
if there exists $Q \succ 0$ and $K(\rho(t)) \in \mathbb{R}^{n_u \times n_x}$ such that
\[
He\{A(\rho) Q + B(\rho) K(\rho) Q\} \prec 0, \quad \forall \rho \in \Theta
\tag{A.52}
\]

\[\blacksquare\]

Theorem A.12. (Quadratic Stabilization of $DT$ LPV systems - State feedback) Consider $DT$ LPV system given in the first equation of (A.1). This $DT$ LPV system is quadratically stable by a state feedback control law given by
\[
u(t) = K(\rho(t)) x(t)
\tag{A.53}
if there exist $Q \succ 0$ and $K(\rho(t)) \in \mathbb{R}^{nu \times nx}$ such that
\[
\begin{bmatrix}
-Q & A(\rho)Q + B(\rho)K(\rho)Q \\
(A(\rho)Q + B(\rho)K(\rho)Q)^T & -Q
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
\]  (A.54)

\begin{theorem}
(Quadratic D-Stabilizability of LPV systems - State feedback) Consider an LMI region given in (A.12). This LPV given in the first equation of (A.1) is quadratically stable by a state feedback control law given by
\[ u(t) = K(\rho(t))x(t) \]  (A.55)

if there exist $Q \succ 0$ and $K(\rho(t)) \in \mathbb{R}^{nu \times nx}$ such that
\[
\begin{bmatrix}
\alpha \otimes Q & \beta \otimes [A(\rho)Q + B(\rho)K(\rho)Q]
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
\]  (A.56)
\end{theorem}

\begin{theorem}
(Quadratic $H_\infty$ State feedback for CT LPV systems) Given the CT LPV system
\[
\begin{align*}
\dot{x}(t) &= A(\rho(t))x(t) + B_1(\rho(t))w(t) + B_2(\rho(t))u(t) \\
z(t) &= C_1(\rho(t))x(t) + D_{11}(\rho(t))w(t) + D_{12}(\rho(t))u(t)
\end{align*}
\]  (A.57)
The CT LPV system (A.57) with state feedback control law has quadratic $H_\infty$ performance $\gamma_\infty$ if there exist $Q \succ 0$ and $K(\rho(t)) \in \mathbb{R}^{nu \times nx}$ such that
\[
\begin{bmatrix}
He[A(\rho)Q + B(\rho)K(\rho)Q] & * & * \\
B_1(\rho)^T & -I & * \\
C_1(\rho)Q + D_{12}(\rho)K(\rho)Q & D_{11}(\rho) & -\gamma^2_\infty I
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
\]  (A.58)
\end{theorem}

\begin{remark}
It is possible to consider $\gamma_\infty$ as a variable, then $\bar{\gamma}_\infty = \gamma^2_\infty$. Consequently, the LMI in Theorem A.14 can be rewritten as follows:
\[
\begin{bmatrix}
He[A(\rho)Q + B(\rho)K(\rho)Q] & * & * \\
B_1(\rho)^T & -I & * \\
C_1(\rho)Q + D_{12}(\rho)K(\rho)Q & D_{11}(\rho) & -\bar{\gamma}_\infty I
\end{bmatrix} \prec 0, \quad \forall \rho \in \Theta
\]  (A.59)
\end{remark}

\section{A.0.2 Observability and Detectability of LPV systems}

\begin{theorem}
(Obsevability) LPV system (A.1) is quadratically detectable, if there exists a matrix $P \succ 0$ and a matrix function $L(\rho)$ such that:
\[
(A(\rho(t)) + L(\rho(t))C)^TP + P(A(\rho(t)) + L(\rho(t))C) \prec 0, \quad \forall \rho(t)
\]  (A.60)
\end{theorem}
A.0.3 Filtering the input

In many cases, the inputs matrices of polytopic LPV systems can be varying and leads to the difficulty in controller designing. However, by using appropriate low-pass filter \[14\] and augmenting the system with the state of the filter, we can change the system to new system with constant inputs matrices.

Given an LPV system

\[
\begin{align*}
\sigma \cdot x (\tau) &= A(\rho (\tau)) x (\tau) + B_1(\rho (\tau)) w (\tau) + B_2(\rho (\tau)) u (\tau) \quad (A.61a) \\
z_\infty (\tau) &= C_1(\rho (\tau)) x (\tau) + D_{11}(\rho (\tau)) w (\tau) + D_{12}(\rho (\tau)) u (\tau) \quad (A.61b) \\
z_2 (\tau) &= C_2(\rho (\tau)) x (\tau) + D_{12}(\rho (\tau)) w (\tau) + D_{122}(\rho (\tau)) u (\tau) \quad (A.61c)
\end{align*}
\]

Define a new control input \( \tilde{u} (\tau) \) such that

\[
\begin{align*}
\sigma \cdot x_u (\tau) &= A_u(\rho (\tau)) x (\tau) + B_u \tilde{u} (\tau) & (A.62a) \\
u (\tau) &= C_u x_u (\tau) & (A.62b)
\end{align*}
\]

where \( A_u(\rho (\tau)) \) is parameter varying stable matrix, while \( B_u \) and \( C_u \) are constant matrices.

From \[A.62\], we obtain new LPV system

\[
\begin{align*}
\begin{bmatrix} \sigma \cdot x (\tau) \\ \sigma \cdot x_u (\tau) \end{bmatrix} &= \begin{bmatrix} A(\rho (k)) & B(\rho (\tau)) C_u \\ 0 & A_u(\rho (\tau)) \end{bmatrix} \begin{bmatrix} x (\tau) \\ x_u (\tau) \end{bmatrix} + \begin{bmatrix} B_1(\rho (\tau)) \\ 0 \end{bmatrix} w (\tau) + \begin{bmatrix} 0 \\ B_u \end{bmatrix} \tilde{u} (\tau) \\
z_\infty (\tau) &= \begin{bmatrix} C_1(\rho (\tau)) & D_{12}(\rho (\tau)) \end{bmatrix} \begin{bmatrix} x (\tau) \\ x_u (\tau) \end{bmatrix} + D_{11}(\rho (\tau)) w (\tau) \\
z_2 (\tau) &= \begin{bmatrix} C_2(\rho (\tau)) & D_{122} \end{bmatrix} \begin{bmatrix} x (\tau) \\ x_u (\tau) \end{bmatrix}
\end{align*}
\]

We can rewrite \[A.61\] as

\[
\begin{align*}
\sigma \cdot \bar{x} (\tau) &= \tilde{A}(\rho (\tau)) \bar{x} (\tau) + \tilde{B}_1(\rho (\tau)) w (\tau) + \tilde{B}_2 \tilde{u} (\tau) \\
z_\infty (\tau) &= \tilde{C}_1(\rho (\tau)) \bar{x} (\tau) + \tilde{D}_{11}(\rho (\tau)) w (\tau) \\
z_2 (\tau) &= \tilde{C}_2(\rho (\tau)) \bar{x} (\tau)
\end{align*}
\]

where

\[
\begin{align*}
\tilde{A}(\rho (\tau)) &= \begin{bmatrix} A(\rho (k)) & B(\rho (\tau)) C_u \\ 0 & A_u(\rho (\tau)) \end{bmatrix}; \tilde{B}_1(\rho (\tau)) &= \begin{bmatrix} B_1(\rho (\tau)) \\ 0 \end{bmatrix}; \tilde{B}_2 = \begin{bmatrix} 0 \\ B_u \end{bmatrix} \\
\tilde{C}_1(\rho (\tau)) &= \begin{bmatrix} C_1(\rho (\tau)) & D_{12}(\rho (\tau)) \end{bmatrix}; \tilde{D}_{11}(\rho (\tau)) = D_{11}(\rho (\tau)) \\
\tilde{C}_2(\rho (\tau)) &= \begin{bmatrix} C_2(\rho (\tau)) & D_{122} \end{bmatrix}
\end{align*}
\]

A.0.4 Controller design for polytopic LPV systems

In this section, we review some results on designing the state feedback controller of the form

\[
u(t) = \sum_{i=1}^{N} \mu_i(\rho(t)) K_i x(t) \quad (A.65)\]
Theorem A.16. (Quadratic $H_\infty$ State feedback for DT LPV systems) Given the DT LPV system

$$x(k+1) = A(x) x(k) + B_1(x) w(k) + B_2(x) u(k)$$

$$z(k) = C_1(x) x(k) + D_{11}(x) w(k) + D_{12}(x) u(k)$$

The CT LPV systems with state feedback control law has quadratic $H_\infty$ performance $\gamma_\infty$ if there exist $Q > 0$ and $K(x) \in R^{n_u \times n_x}$ such that

$$\begin{bmatrix} Q & A(x) Q + B(x) K(x) & B_1(x) \\ * & Q & 0 \\ * & * & I \end{bmatrix} \begin{bmatrix} 0 \\ Q C_1(x)^T + Q K(x)^T D_{11}(x)^T \\ D_{11}(x) \end{bmatrix} \succ 0, \quad \forall \rho \in \Theta$$

(A.68)

Theorem A.17. (Quadratically stabilizing polytopic state-feedback controller for CT LPV systems) The CT LPV system is quadratically stable by a state feedback of the form (A.65) if there exist $Q > 0$ and $\Gamma_i \in R^{n_u \times n_x}, i = 1,...,N$ such that

$$\begin{bmatrix} -Q & A_i Q + B_i \Gamma_i \\ (A_i Q + B_i \Gamma_i)^T & -Q \end{bmatrix} \prec 0, \quad \forall i = 1,...,N$$

(A.69)

Then the polytopic state feedback control gain can be calculated as $K_i = \Gamma_i Q^{-1}, \forall i = 1,...,N$.

Theorem A.18. (Quadratically stabilizing polytopic state-feedback controller for DT LPV systems) The DT LPV system is quadratically stabilizable by a state feedback of the form (A.65) if there exist $Q > 0$ and $\Gamma_i \in R^{n_u \times n_x}, i = 1,...,N$ such that

$$He \{ A_i Q + B_i \Gamma_i \} \prec 0, \quad \forall i = 1,...,N$$

(A.70)

Then the polytopic state feedback control gain can be calculated as $K_i = \Gamma_i Q^{-1}, \forall i = 1,...,N$.

Theorem A.19. (Quadratically D-stabilizing polytopic state-feedback controller for LPV systems) Given an LM region $D$ defined as in (A.13). Let $Q > 0$ and $\Gamma_i \in R^{n_u \times n_x}, i = 1,...,N$ such that

$$\alpha \otimes Q + He \{ \beta \otimes (A_i Q + B_i \Gamma_i) \} \prec 0, \quad \forall i = 1,...,N$$

(A.71)
Appendix A. Preliminaries

Then, the closed-loop system made up by the LPV system (A.1) for the case $B(\rho(t)) = B$ and polytopic system matrices in (A.66) and the polytopic state-feedback control law given by (A.65) with the gains calculated as $K_i = \Gamma_i Q^{-1}$, $i = 1, ..., N$, is quadratically D stable. ■

**Theorem A.20.** (Quadratic $H_\infty$ polytopic statefeedback control for CT LPV systems [191])
The polytopic CT LPV is quadratically stabilizable by a state feedback of the form (A.65) if and only if there exist a matrix $Q > 0$ and $\Gamma_i \in \mathbb{R}^{n_u \times n_x}$, $i = 1, ..., N$ such that

$$
\begin{bmatrix}
H e \{ A_i Q + B \Gamma_i \} & * & * \\
B_{1,i}^T & -I & * \\
C_{1,\infty} Q + D_{1,\infty} 2 \Gamma_i & D_{1,\infty} & -\gamma_2 \infty I
\end{bmatrix} \prec 0, \ \forall i = 1, ..., N \quad (A.72)
$$

Moreover, the state feedback control law given by (A.65) with matrices $K_i = \Gamma_i Q^{-1}$, $\forall i = 1, ..., N$ has the quadratic $H_\infty$ performance $\gamma_\infty$. ■

**Theorem A.21.** (Quadratic $H_\infty$ polytopic statefeedback control for DT LPV systems [191])
The polytopic DT LPV is quadratically stabilizable by a state feedback of the form (A.65) if and only if there exist a matrix $Q > 0$ and $\Gamma_i \in \mathbb{R}^{n_u \times n_x}$, $i = 1, ..., N$ such that

$$
\begin{bmatrix}
Q & A_i Q + B \Gamma_i & B_{1,i} & 0 \\
* & Q & 0 & QC_{1, \infty}^T \\
* & * & 0 & I \\
* & * & * & \gamma_2 \infty I
\end{bmatrix} \prec 0, \ \forall i = 1, ..., N \quad (A.73)
$$

Moreover, the state feedback control law given by (A.65) with matrices $K_i = \Gamma_i Q^{-1}$, $\forall i = 1, ..., N$ has the quadratic $H_\infty$ performance $\gamma_\infty$. ■
Clustering or cluster analysis is the task of dividing the data points or objects into groups (called clusters) in such a way data points in the same cluster are more similar (in some sense) to other data points in the same group than the other data points in other clusters.

- **Density-Based Methods**: Density-based Clustering methods are the clustering methods that are based on detecting areas where points are concentrated and where they are separated by areas that are empty or sparse. The data points, that do not belong to any cluster, are considered as noise. Density-based Clustering methods have good accuracy and ability to merge two clusters. Some representatives of Density-based Clustering methods are DBSCAN (Density-Based Spatial Clustering of Applications with Noise) [67], OPTICS (Ordering Points to Identify Clustering Structure) [251], etc.

- **Hierarchical Based Methods** [163]: The clusters formed in these methods form a tree-type structure based on the hierarchy. New clusters are formed using the previously formed one. Hierarchical based clustering methods can be divided into two main types:
  - Agglomerative clustering (bottom-up approach) [4]: An object is initially considered as a single-element cluster (leaf). The two most similar clusters are combined into a new bigger cluster (nodes) at each step of the algorithm. Then, this procedure is repeated till all the data points belong to just one single big cluster (called root). Result of agglomerative clustering method is the tree which can be plotted as a dendrogram.
  - Divisive hierarchical clustering (top-down approach) [242]: This algorithm is in an inverse order of Agglomerative clustering. The algorithm starts with the root, in which all objects are included in a single cluster. The most heterogeneous cluster is divided into two clusters at each iteration step. The process is repeated until all objects are in their own cluster.

Some examples of Hierarchical clustering Based Methods are CURE (Clustering Using Representatives) [90], BIRCH (Balanced Iterative Reducing Clustering and using Hierarchies) [248], etc.

- **Partitioning clustering Methods**: are the clustering methods that partition the objects into groups based on their similarity and each partition forms one cluster. This
Appendix B. Clustering method

method is commonly implemented by optimizing an objective criterion similarity function especially when the distance is a major parameter. Some examples of Partitioning clustering Methods are K-means [146][173], CLARANS (Clustering Large Applications based upon Randomized Search) [159], K-medoids clustering or PAM [119].

- **Grid-based clustering Methods**: are the clustering methods where the data space is divided into a finite number of cells that form a grid-like structure. All the clustering operation performed on these grids are fast and independent of the number of data objects. Some examples of Grid-based clustering Methods are STING (Statistical Information Grid) [234], wave cluster [207], CLIQUE (CLustering In Quest) [165], etc.
Minimal convex polygon decomposition

A partition of a polygon $P$ is a set of primitive units (or polygons, these primitive units can be triangles, rectangles, squares, convex or concave polygons) such that these polygons do not intersect each other and the union of these polygons is exactly equal to the interior of the original polygon $P$. A polygon partition problem is a problem of finding a partition which is optimal in some sense. The optimal criterion for this polygon partition problem can be partition with a smallest number of polygons, with polygons of smallest total side-length, or minimal number of convex polygons.

Polygon partitioning is a really important class of problems in computational geometry because most geometric problems are simpler and faster on convex objects than on non-convex ones. There exists a number of different polygon partitioning problems. They are depending on the type of polygon that is being partitioned and also on the types of units (polygons) allowed for partitioning.

The term polygon decomposition is often used as a general term that includes both covering and partitioning[143].

Polygon decomposition has been widely applied in several areas:

- Polygon decomposition has been widely used in computational geometry. Generally, problems that restrict the types of polygons such as convex or star-shaped are always simpler than the ones with general polygons. Therefore, for computational geometry problems, polygons are first decomposed into simpler component parts. Then, the algorithm is applied to the gathered simpler polygons. Finally, partial solutions are combined to get the full solution. Examples can be seen in [164] [8].

- Very large-scale integration (VLSI) is the procedure for generating an integrated circuit (IC) by combining millions of MOS transistors onto a single chip. Layouts are illustrated as polygons [137] in VLSI data processing, and one method for preparing the electron-beam lithography is to decompose these polygon regions into fundamental simple polygons. Polygon decomposition is also applied for dividing the routing region into channels.

- Pattern recognition [25] is the process of recognizing patterns by using machine learning algorithm. These techniques extract information from an object for identifying, classifying, or describing it. General polygons are usually recognized by decomposing
Appendix C. Minimal convex polygon decomposition

it into simpler components, then identify the components and their interrelationships. Finally, the gathered information is used to determine the shape of the object.

- Some others applications of Polygon decomposition include image processing [153], computer graphics [222], database systems [132], and data compression [139].

Several methods for polygon decomposition are:

- Partitioning a polygon to triangles [1] [117]
- Partitioning a polygon to pseudo-triangles [10] [96]
- Partitioning a rectilinear polygon into rectangles [52]
- Partitioning a polygon to trapezoids [39] [16]
- Partitioning a polygon to convex quadrilaterals [187] [145]
- Partitioning a polygon to m-gons [131] [125]
The Computational Geometry Algorithms Library (CGAL) is an open source software library of computational geometry algorithms that provides easy access to efficient and reliable geometric algorithms in the form of a C++ library. It was initially released in 1996 and primarily written in C++. Nowadays, CGAL libraries are also available for Python and Java.

CGAL is used and applied in a number of areas that require geometric computation such as computer vision, medical imaging, computer-aided design, geographic information system, molecular biology, and robotics.

The CGAL library covers the following topics:

- Geometry kernels - basic geometric operations on geometric primitives
- Arithmetic and algebra
- Convex hull algorithms
- Polygons and polyhedra
- Polygon and polyhedron operations
- Arrangements
- Point set triangulations
- Delaunay triangulations
- Voronoi diagrams
- Mesh generation
- Geometry processing
- Search structures
- Shape analysis, fitting, and distances
- Interpolation
- Kinetic data structures
The main CGAL package was used in this thesis is '2D Polygon Partitioning'. This package provides functions for partitioning polygons in monotone or convex polygons. The algorithms can produce results with the minimal number of polygons, as well as approximations which have no more than four times the optimal number of convex pieces but they differ in their runtime complexities.


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**Titre:** Planification et Commande robustes de véhicules aériens sans pilote

**Mots clés:** Systèmes multi-modèle Takagi-Sugeno, Commande robuste, Planification et suivi de trajectoire, Mission coordonnée, Optimisation énergétique, Commande déportée

**Résumé:** L’objectif de cette thèse est de réaliser la modélisation, la planification de trajectoire et le contrôle d’un robot hélicoptère sans pilote pour la surveillance de grandes surfaces, en particulier dans des applications d’agriculture de précision. Plusieurs tâches de l’agriculture de précision sont abordées. Dans les missions de surveillance des ravageurs, les drones seront équipés de caméras spécialisées. Une trajectoire sera recherchée et créée pour permettre aux aéronefs sans pilote de capturer des images de zones de cultures entières et d’éviter les obstacles pendant le vol. Les zones infectées seront ensuite identifiées en analysant les images prises. Lors de la pulvérisation d’insecticides, l’aéronef doit être contrôlé pour voler selon une trajectoire préprogrammée et pulvériser l’insecticide sur toutes les zones de culture infectées.

Dans la première partie, nous présentons un nouvel algorithme de planification de chemin de couverture complet en proposant une nouvelle décomposition cellulaire qui repose sur une généralisation de la variante Boustrophédon, à l’aide de fonctions Morse, avec une extension de la représentation des points critiques. Cette extension conduit à un nombre réduit de cellules après décomposition. L’algorithme génétique (GA) et l’algorithme de problème du voyageur de commerce (TSP) sont ensuite appliqués pour obtenir le chemin le plus court pour une couverture complète. Ensuite, à partir des informations sur la carte concernant les coordonnées des obstacles, des zones infectées et non infectées, les zones infectées sont divisées en plusieurs régions non chevauchantes en utilisant une technique de regroupement. Ensuite, un algorithme est proposé pour générer le meilleur chemin pour qu’un véhicule aérien sans pilote (UAV) distribue des médicaments à toutes les zones infectées d’un environnement agricole qui contient des obstacles non convexes, des zones exemptes de parasites et des zones infectées de parasites.

Dans la deuxième partie, nous étudions la conception d’un système de contrôle robuste qui permet au véhicule de suivre la trajectoire prédéfinie d’un hélicoptère à modèle dynamique variable en raison des changements de coefficients dynamiques tels que la masse et les moments d’inertie. Par conséquent, les lois robustes d’observation et de contrôle sont nécessaires pour adopter les changements des paramètres dynamiques ainsi que l’impact des forces externes. La méthode proposée consiste à explorer les techniques de modélisation, de planification et de contrôle par l’approche LPV. Pour avoir des algorithmes facilement implantables et adaptables aux changements de paramètres et de conditions d’utilisation, nous privilégions la synthèse de l’Observateur d’Entrées Inconnues (UIO) à Paramètre Linéaire Variable (LPV), et des contrôleurs retour d’état quadratique LPV, retour d’état robuste et retour de sortie statique. L’observateur et les contrôleurs sont conçus en résolvant un ensemble d’inégalités matricielles linéaires (LMI) obtenues à partir du lemme réel borné et de la caractérisation des régions LMI.

Enfin, pour mettre en évidence les performances des algorithmes de planification de trajectoire et des lois de contrôle générées, nous effectuons une série de simulations à l’aide de MATLAB Simulink. Les résultats de la simulation sont assez prometteurs. L’algorithme de planification de trajectoire de couverture suggère que la trajectoire générée raccourcit la distance de vol de l’aéronef mais évite toujours les obstacles et couvre toute la zone d’intérêt. Les simulations pour l’observateur LPV UIO et les contrôleurs LPV sont effectuées avec les cas où la masse et les moments d’inertie changent brusquement et lentement. Le LPV UIO est capable d’estimer les variables d’état et les perturbations inconnues et les valeurs estimées convergent vers les vraies valeurs des variables d’état et les perturbations inconnues de manière asymptotique. Les contrôleurs LPV fonctionnent bien pour divers signaux de référence (impulsion, aléatoire, constant et sinusoïdale) et plusieurs types de perturbations (impulsionnelle, aléatoire, constante et sinusoïdale).
Robust planning and control of unmanned aerial vehicles

Keywords: Takagi-Sugeno Multi-model systems, robust control, trajectory planning and tracking, coordinated mission, optimization in energy

Abstract: The objective of this thesis is to realize the modeling, trajectory planning, and control of an unmanned helicopter robot for monitoring large areas, especially in precision agriculture applications. Several tasks in precision agriculture are addressed. In pest surveillance missions, drones will be equipped with specialized cameras. A trajectory will be researched and created to enable unmanned aircraft to capture images of entire crop areas and avoid obstacles during flight. Infected areas will be then identified by analyzing taken images. In insecticides spraying, the aircraft must be controlled to fly in a pre-programmed trajectory and spray the insecticide over all the infected crop areas.

In the first part, we present a new complete coverage path planning algorithm by proposing a new cellular decomposition which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a reduced number of cells after decomposition. Genetic Algorithm (GA) and Travelling Salesman Problem (TSP) algorithm are then applied to obtain the shortest path for complete coverage. Next, from the information on the map regarding the coordinates of the obstacles, non-infected areas, and infected areas, the infected areas are divided into several non-overlapping regions by using a clustering technique. Then an algorithm is proposed for generating the best path for a Unmanned Aerial Vehicle (UAV) to distribute medicine to all the infected areas of an agriculture environment which contains non-convex obstacles, pest-free areas, and pests-ridden areas.

In the second part, we study the design of a robust control system that allows the vehicle to track the predefined trajectory for a dynamic model-changing helicopter due to the changes of dynamic coefficients such as the mass and moments of inertia. Therefore, the robust observer and control laws are required to adopt the changes in dynamic parameters as well as the impact of external forces. The proposed approach is to explore the modeling techniques, planning, and control by the Linear Parameter Varying (LPV) type technique. To have easily implantable algorithms and adaptable to changes in parameters and conditions of use, we favor the synthesis of Linear Parameter Varying (LPV) Unknown Input Observer (UIO), LPV quadratic state feedback, robust state feedback, and static output feedback controllers. The observer and controllers are designed by solving a set of Linear Matrix Inequality (LMI) obtained from the Bounded Real Lemma and LMI regions characterization.

Finally, to highlight the performances of the path planning algorithms and generated control laws, we perform a series of simulations in MATLAB Simulink environment. Simulation results are quite promising. The coverage path planning algorithm suggests that the generated trajectory shortens the flight distance of the aircraft but still avoids obstacles and covers the entire area of interest. Simulations for the LPV UIO and LPV controllers are conducted with the cases that the mass and moments of inertias change abruptly and slowly. The LPV UIO is able to estimate state variables and the unknown disturbances and the estimated values converge to the true values of the state variables and the unknown disturbances in asymptotically. The LPV controllers work well for various reference signals (impulse, random, constant, and sine) and several types of disturbances (impulse, random, constant, and sine).