



Localization of a collaborative underwater sound source in a shallow environment.

Pedro Eugenio Martins de Magalhaes

► To cite this version:

Pedro Eugenio Martins de Magalhaes. Localization of a collaborative underwater sound source in a shallow environment.. Acoustics [physics.class-ph]. Université Grenoble Alpes, 2018. English. NNT : 2018GREAU042 . tel-02043446

HAL Id: tel-02043446

<https://theses.hal.science/tel-02043446>

Submitted on 21 Feb 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

THÈSE

Pour obtenir le grade de

DOCTEUR DE LA COMMUNAUTE UNIVERSITE GRENOBLE ALPES

Spécialité : **Traitement du signal, localisation cible sous-marine Signal**

Arrêté ministériel : 25 mai 2016

Présentée par

Pedro Eugenio Martins de Magalhaes

Thèse dirigée par **Jérôme MARS** codirigée par **Cornel IOANA** et **Xavier CRISTOL**, préparée au sein du **Grenoble Images Parole Signal Automatique (GIPSA-Lab)** dans l'Ecole Doctorale Terre Univers Environnement

Localisation d'une source sonore sous-marine collaborative dans un environnement peu profond

Thèse soutenue publiquement le **5 Novembre 2018**,
Devant le jury composé de :

M. Sergio JESUS

Président du jury, Professeur, Université de Algarve

M. Pascal LARZABAL

Rapporteur du jury, Professeur, Ecole Normale Supérieure de Cachan

Mme. Barbara NICOLAS

Rapporteur du jury, Professeur, Creatis - Université Lyon

M. Dominique FATTACCIOLI

Membre du jury, Chargé de recherche DGA Systèmes Navals

M. Jérôme MARS

Directeur, Professeur, GIPSA-lab. - Université de Grenoble

M. Xavier CRISTOL

Co-Directeur, Chargé de recherche, Thales Underwater Systems

M. Cornel IOANA

Invité Co- encadrant, Professeur, GIPSA-lab. - Université de Grenoble

M. Bruno CHALINDAR

Invité Co- encadrant, Chargé de recherche, Thales Underwater Systems



THE S I S

Localization of a collaborative underwater sound source in a shallow environment.

Presented and defended by

Pedro Eugenio Martins de MAGALHAES

for jointly obtaining the

DOCTORATE DEGREE

of University of Grenoble

Doctoral School Earth Universe Environment

Specialization: Signal processing, Underwater target localization

Thesis directed by Jerome MARS, Xavier CRISTOL and Cornel IOANA.

Prepared in the Grenoble Image Parole Signal Automatique laboratory (GIPSA-lab).

Defended in Grenoble, on 5th November 2018, in front of the jury:

Reviewers :

Mr Sergio JESUS

President of the jury, Professor, University of Algarve

Mr Pascal LARZABAL

Rapporteur of the jury, Professor, Ecole Normale Supérieure of Cachan

Mrs. Barbara NICOLAS

Rapporteur of the jury, Professor, Creatis - University Lyon

Mr Dominique FATTACCIOLI

Member of the jury, Research Scientist, DGA Naval Systems

Mr Jérôme MARS

Director, Professor, GIPSA-lab. - University of Grenoble

Mr Xavier CRISTOL

Co-Director, Research Scientist, Thales Underwater Systems

Mr Cornel IOANA

Co-supervisor, Professor - University of Grenoble

M. Bruno CHALINDAR

Co-supervisor, Research Scientist, Thales Underwater Systems

Acknowledgements

This thesis represented the biggest challenges in my life and today, after an intensive period of three years symbolizes the end of my journey in obtaining my Ph.D. It has been a period of intense learning and definitely has had a big impact on me, not only scientifically, but also on a personal matter. I would like to reflect on all the people involved and how it would not have been possible without their contribution.

Firstly, I would like to express my sincere and deepest gratitude to my supervisor Dr Xavier Cristol for his patience, support, and for sharing his immense knowledge with me during the course of this research. I have lost the counting of the numerous time I spent in his office and I must say that his willingness to give his time and care so generously has been very much appreciated. You have been a tremendous mentor for me. I would like to express my special appreciation and thanks to my supervisor Dr. Jerome Mars who kept a sense of humor when I had lost mine. Without his enthusiasm, encouragement, support and continuous optimism, this thesis would hardly have been completed. I also would like to thank you for all the discussions we had including meeting on holidays and for what you did in Japan. I must say that I consider both of you more than my supervisors but as friends. I owe my gratitude to my supervisor Dr. Cornel Iaona for providing the equipment's to the experiment on GIPSA-LAB and comments. To all of you I would like to thank for the valuable and constructive suggestions and discussions during the planning and development of this research work and for comments that greatly improved the manuscript. Besides my supervisors, I would like to thank the rest of my thesis committee for your generously time offered me and for your comments and suggestions toward improving this work.

I wish to thank the company to make me growing fast and more robust professionally. I also would like to thank the invaluable criticism and the many times in which my work was disbelieved due to the good results achieved, without a doubt this reluctance allowed me to improve my presentation skills. I want to thank the DGA Naval Systems for their contributions in collecting the data and in providing details of the Alma 2015 experiment and also thank the captain and the crew of the COMEX research vessel Janus, which sailed during the ALMA 2015 campaign.

I want to thank my French friends Gaultier, Alexis, Melisandre, Nicolas and Pierre and his family to show me that there is still hope in friendship towards different nationalities. I also want to thank my friends: Jithandra, Karina, Liza, Michel, Pedro, Tien, Anton, Paula, Raphael, Vinicius, Renato, Nicole, Daiane, Ion, Milena, Leni, and Kieran among others for their support and for all the fun we have had during this time allowing me to keep my sanity.

It is difficult to overstate my gratitude to perhaps the most important and wonderful person during my Ph.D. Estelle Vonachen supported and helped me so much throughout this period that it is just impossible to describe all the situations. With her optimism and motivation she showed me that even the most difficult situations can be overcome. Definitely, she had a big contribution pushing me towards to conclude this work. If I didn't end up in a madhouse during this time it was thanks to her. My sincere thank you.

Finally, I must express my very profound gratitude to my parents, especially to the figure of my mother Celina, who raised me given all that I needed, and my sister Fernanda, for providing me with support, and unconditional trust. Words cannot express how grateful I am to you for all of the sacrifices that you both have made on my behalf. Your prayer and the certainty that you were there for me was what sustained me thus far.

I want to thank in memory of Ayrton Senna for his inspiration and for showing that we can be proud as a Brazilian and with a hard work we can be one of the best. Words of thanks and appreciation will always be few to all those who were involved on this incredible journey helping me to make this thesis possible in these years of research.

CHAPTER 1	5
1.1. Introduction	5
1.2. Inverse problem	6
1.3. Simulation program	8
1.3.1 Ray path theory.....	9
1.4. Sound Speed Profile.....	10
1.4.1 Propagation Loss	10
1.4.2 Geometric spreading loss	11
1.4.3 Absorption loss.....	11
1.4.4 Bottom Loss	12
1.4.5 Scattering loss.....	13
1.5. Chapter Summary	15
CHAPTER 2	16
2.1. Introduction	16
2.2. Historical survey presented at the literature	17
2.3. Definition	19
2.3.1 Green's function	22
2.3.2 Covariance matrix estimation.....	23
2.4. Matched field signal processors.....	24
2.4.1 Bartlett (conventional) MFP processor.....	24
2.4.2 MVDR-MFP processor	25
2.5. Matched field tomography - MFT	25
2.6. Chapter Summary	26
CHAPTER 3	28
3.1. Introduction	28
3.2. Definition	30
3.2.1 Maximum Hausdorff Distance	30
3.2.2 Mean Hausdorff Distance.....	32
3.2.3 Partial Hausdorff Distance	33
3.2.4 Median Hausdorff Distance.....	34
3.2.5 Combination of Hausdorff distance.....	34
3.3. Probabilistic formulation HD	35
3.4. Hausdorff distance temporal Translation	35
3.5. Rasterized of grid of simulation	36
3.6. Hierarchical Cell Decomposition	36
3.7. Gromov Hausdorff distance	37
3.8. Chapter Summary	38
CHAPTER 4	39

4.1.	Introduction	39
4.2.	Measurement Setup	40
4.3.	Simulation Results	46
4.4.	Experimental results.....	48
4.5.	Chapter Summary	51
CHAPTER 5		53
5.1.	Introduction	53
5.2.	The ALMA 2015 experiment	54
5.3.	Spatial diversity versus beamforming	58
5.4.	Results with only one hydrophone	61
5.5.	Results with Array - Spatial diversity.....	67
5.5.1	SSP close to the source	70
5.5.2	SSP close to the receiver.....	73
5.6.	Best Configuration.....	78
5.7.	Minimal number of Hydrophones.....	79
5.8.	Chapter Summary	81
CHAPTER 6		83
6.1.	Introduction	83
6.2.	Beamforming.....	85
6.3.	Results Adaptive synchronization	86
6.3.1	SSP close to the Source	91
6.3.2	SSP close to the Receiver.....	96
6.4.	Minimal number of Hydrophones.....	101
6.5.	Best Configuration.....	103
6.6.	Cramer Rao bound.....	104
6.7.	Array Section	109
6.8.	Chapter Summary	112
CHAPTER 7		113
APPENDIX A		121
APPENDIX B		123
APPENDIX C		125
APPENDIX D		129
APPENDIX E		130
APPENDIX F.....		132
APPENDIX G		137
APPENDIX H		145
Résumé étendu.....		147

'Picking up the quiet hum of a battery-powered, diesel-electric submarine in busy coastal waters is like trying to identify the sound of a single car engine in the din of a major city'

***Rear Admiral Frank Drennan
Commander of the Naval Mine and Anti-Submarine Warfare.***

Introduction

About 71 percent of the Earth's surface is water-covered, and the oceans hold about 96.5 percent of all Earth's water. About half of the world's population lives within 200 kilometers of a coastline, and their numbers are expected to double by 2025. Based on global, regional and local operations of international, national, and commercial organizations, Confined and Shallow Waters (CSW) is priority area of interest linking the high seas to the coasts. Maritime transport is essential to the world's economy as over 90% of the world's trade is carried by sea. Seaports are the backbone of global transportation routes where all shipping operations begin and end. 75% of all trade goes through at least one narrow passageway of water and therefore vulnerable strait, such as the Hormuz strait and Gibraltar strait, among others. Even the transoceanic traffic is partially carried out by narrow straits. Therefore, narrow straits, jagged coastlines, and archipelago-like environments, is to be regarded as a very specific operational environment with a broad variety of activities, threats and particularities which considerably affect the conduct of military operations. In such cases, any shipping company is at risk of being easily hampered or even disturbed. [1]

Over the past decade, the location of passive sonars and the tracking of underwater acoustic targets have attracted increasing interest. However, this still difficult problem remains a constant research theme, having a high strategic value for naval operations, particularly in the protection of coastal oceans. The requirements of the naval mission have been extended from open-ocean warfighting operations, which consists of The traditional warfare tasks of anti-air, anti-surface, antisubmarine, strike, and mine warfare, to shallow-water (or littoral) scenarios capable of defeating anti-access and asymmetric threats (terrorists, pirates, or organized criminals). This transition has not been easy for sonar technologists because the sonar systems originally designed for the high seas warfare now have to adapt to work in coastal areas. This has also been the case for modeling and simulation technologies, which have been redefined and refocused to support a new generation of naval systems designed to operate effectively in coastal areas while maintaining deep water capacity. Shallow water geometry, with a maximum depth of 200 m, increases the importance of boundary interactions, which reduce acoustic energy through propagation losses. The interfering noise combined with boundary reverberation makes the detection of the desired signals of interest a really difficult task to achieve. Coastal operations present operators with a unique, demanding and growing challenge, and require rethinking the wide range of naval roles and missions, both offensive and defensive. [2] [3]

“CSW is a cramped, congested and contested operational environment constituting an extremely complex thus challenging littoral joint battlespace which affects the freedom of movement and action by specific geographical and geophysical factors as well as manifold threats and risks. On the other side, CSW also offers a broad range of possibilities and opportunities for military operations.” NATO 2016 [4]

A complete and up-to-date tactical picture is essential to the successful execution of the overall mission. Surveillance can provide the commander with accurate information about the adversary's operations, his possibly intentions and threats, his valuable target location and his force disposition. Timely and comprehensive identification, tracking, and preemptive attack of submarine threats even before they leave port are major naval priorities. Naval forces conducting CSW operations should have robust tools at hand giving all sources of information to provide an effective comprehensive situational awareness. The early the

identification and location of the possible threat, the greater is the advantage on the battlefield providing an undersea dominance, especially now after the recent threat of supercavitating torpedo technology. The idea behind of this thesis is to make the localization and possible identification reliable in any operation scenario allowing the commander take the best decision to their missions.

There are two generic approaches for exploiting and measuring underwater sound waves, and both active and passive sonars were developed during the war:

Passive sonars, first developed in 1490 by Leonardo da Vinci, are listening devices, no energy is transmitted to the underwater channel, consisting of single hydrophones or arrays of hydrophones, used primarily to detected sound from the radiated signature levels from the propeller, active sonar, inadvertently sound by the target, and also to detect marine animals like whales for scientific applications, without revealing its own location. Tactical systems consist of sonobuoys dropped into the ocean from ships and aircrafts, hullmounted and long towed arrays from submarine and surface vessels. Two important systems named as: the Surveillance Towed Acoustic Sensor System (SURTASS) and the Sound Surveillance System (SOSUS) were develop by the U.S. to missions of Anti-Submarine Warfare (AWS), which include providing indications and warning of increased submarine activity. "The more we have been faced with the challenge of diesel submarines and shallow water, the more we have come to realize the importance of the multi-sensor approach to ASW", said Vice Admiral Owens [2]. The SOSUS played an important role in 1968 when by trilateration was able to locate the Soviet submarine which exploded close to the Hawaii. Although it has been shown the efficiency of this system, its implementation and maintenance is considered too expensive. Nowadays more robust sensors have been developed using optic fiber networks.

Active sonars, developed in 1918, by both Britain and the U.S, first designed after the Titanic disaster to detect the presence of large objects under water as an attempt to avoid that it ever happen again. It emits an acoustic signal or pulse of sound, often called a "ping" into the underwater channel. These sound waves propagate through the ocean environment to the target, and then the sound bounces off the object and propagate back an "echo" to the receiving hydrophones. . By determining the time between the emission of the sound pulse and its reception, it is possible to determine the range and orientation of the object. The active sonars used during World War II achieved only short detection ranges against German submarines because of the high frequencies used. Although the technical designs of these sonars were made more manageable, using high-frequency transducers, the long detection ranges associated with surveillance require lower operating frequencies because sound absorption in seawater is dependent on frequency. For this reason, low-frequency active acoustics (LFAA) with frequency of 100 to 1000 kHz, which can travel much longer, has been receiving more attention by researches. There are two primary uses of active sonar: first used to detection and tracking other vessels and second used to navigation or obstacle avoidance. In a tactical situation is only used to verify a final range to a target in which it is desired to engage with a torpedo. More recently, the active sonar has been used to matched topography processing to determine the geoacoustic parameters involved in its propagation. The use of sound to explore the ocean and the sea floor contributes to an increased sonar performance. A better knowledge of the underwater sound propagation and the ambient noise properties gives the submarine crew the ability to hide and seek.

Objective

As demonstrated in past wars and conflicts, new technologies have a significant impact on combat outcomes. Thus the consequent utilization of new technologies to detect threats, particularly interested in shallow water environment, is of paramount importance for naval operations. The purpose of this thesis is to detect and localize a surface and sub-surface target using a passive sonar configuration mounted in a moving platform such as a submarine. The proposed technique was tested in a controlled environment using both a cooperative and non-cooperative system, and in an at-sea operational environment, tested only using a cooperative system. The Hausdorff Distance technique proposed here is faster, precise and robust technique to target localizations even when in presence of underwater propagation mismatches, which is the primary limitation to the use of Matched Field Processing (MFP).

Organization

This work is divided in 7 chapters. In Chapter 1, we briefly review several related theories used for this thesis. The inverse problem was presented as well as the ray path propagation theory. At the end of the chapter the Sound Speed Profile is presented as well as the propagation loss on the ocean. In Chapter 2, we review localization techniques, given a special attention to the Matched field processing MFP. In Chapter 3, we define the Hausdorff distance and adapt to be used as minimal cost function to underwater target localization. In Chapter 4, we show the results from the controlled experiment performed at the GIPSA-LAB. The Chapter 5 introduced the concept of spatial diversity with the application of the Hausdorff Distance in an at-sea experiment called ALMA 2015. Chapter 6 introduced the concept of beamforming. The comparison between both processes was presented at the end of the chapter. Finally, Chapter 7 presents the conclusions of the thesis and gives some suggestions for future work.

CHAPTER 1

Localization as inverse Problem

Contents

1.1. Introduction	5
1.2. Inverse problem	6
1.3. Simulation program	8
1.3.1 Ray path theory.....	9
1.4. Sound Speed Profile.....	10
1.4.1 Propagation Loss	10
1.4.2 Geometric spreading loss	11
1.4.3 Absorption loss.....	11
1.4.4 Bottom Loss	12
1.4.5 Scattering loss.....	13
1.5. Chapter Summary	15

1.1. Introduction

The ocean is an irregular and inhomogeneous acoustic waveguide bounded above by the sea surface and below by the seabed [4]. The context of shallow waters, typically a maximum depth of 200 m, associated with a long range of targets, produces sonar signals along the multiple paths at a very close angle and the travel time one of the other. The SSP for this scenario is refractive downwards or nearly constant over depth, resulting in long-distance multipath propagation exclusively via numerous interactions with complex boundaries (rugged seabed, rough moving sea surface), culminating to a tremendous obstacle for achieving an accurate ranging of the target. Non-stationary more or less random interference patterns, which can be either constructive (gain) or destructive (fading), affect the performance of the signal processing. The signal received by each sonar sensor is assumed to be the sum of the copies of the waveform transmitted by the target. It contains information about the specific range and depth of the target across the characteristics of the different propagation paths. The location information of the target can be inferred from two widely used parameters: the arrival time difference (TDOA) and / or the arrival angles (AOA).

Spatial and temporal dependencies relate to how acoustic parameters of oceans vary with geo-location and time. Oceanographic parameters in coastal environments are generally characterized by strong spatial and temporal variability, which makes these regions very difficult acoustic environments. The term uncertainty is used to refer to how well is the knowledge of the parameter behavior, which is always incomplete to some degree.

Uncertainties in environmental parameters may affect all features of the marine medium: changes in temperature, pressure and salinity, the main parameters of the sound speed profile affect the refraction of sound in the water column (fronts, upwelling, tides, internal waves, , currents and turbulence) influences the times and angles of arrival from the multipath; seabed topography (micro-topography, ripples) affects bottom reflection angles; sea bottom geo-acoustic properties like sediment type or layering of the seafloor affect reflection coefficient and may impact the detectability of late arrivals; the sea surface affected by gravity waves is an intrinsically random boundary and affects both reflection coefficients and arrival angles. In shallow water, interactions of the acoustic fields with the seabed require an increase of understanding of the sedimentary structure of the bottom much higher than the one required in deep-water environments. In many cases, even a small variation in one of these items can change dramatically the propagation paths. [5]

Seasonal variations affect oceanographic parameters in the upper ocean. In addition, all these parameters are geographically dependent. Episodic transitions of meteorological fronts from continental interiors affect the thermal structure of the adjacent shelf waters through intense air-sea interactions [6]. Diurnal changes also affect oceanographic parameters. In the hottest part of the day, the temperature rises near the surface and, as a result, the SSP increases towards the sea surface. This heating close to the surface (and its subsequent cooling) has a profound effect on surface-ship sonars. Thus, the diurnal heating causes lower sonar performance in the afternoon, a phenomenon known as the afternoon effect [7]. Others problems came by river due to its strong salinity gradients along the adjacent coast. Variable bottom topographies also complicate acoustic bottom boundary conditions [3].

This chapter is divided into three parts: the first one examines the process of solving the inverse localization problem, the second concerns acoustic propagation models and the last shows the influence of propagation losses, noise and SSP.

1.2. Inverse problem

The principle of most accurate technique to inverse localization is achieved by solving the acoustic wave equation and requires a two-steps procedure:

- The first step consists of predicting the accurate replica of the acoustic signals and the corresponding TDOA and/AOA modeled, with the help of an acoustic propagation models (rays theory, Normal modes, parabolic equation, multipath expansion, wavenumber integration.). Each of techniques has its unique field of application which can be defined in terms of acoustic frequency and environmental complexity [3]. This modeled information is then used as a reference for the comparison with the measured signal and sharply depend on the accuracy of the a priori knowledge of the input environment parameters, so it is not surprising that processor performance depends on the accuracy and resolution of the environmental models.
- The second step consists of finding the target location that produces the best match between the modeled signal parameters and the measured one, process called model-based signal processing; this best matching may be searched and achieved using different optimizations methods and criteria at the literature, such as Matched field processing and Matched mode processing (see chapter 2), and the proposed Hausdorff distance (see chapter 3). The combination of several hydrophones improves and makes more robust the localization

processing and its accuracy by making use of spatial diversity, as a remedy to the problem of multipath interference and fading.

For the applicability of Haurdorff distance one additional step must be included, which consist of extracting the information of the TDOA and AOA as shown at Fig. 1. When the waveform parameters are known or can be estimated, the most popular method for estimating the TDOA is a so-called matched filtering (correlation of signal with estimated waveform) [8], however can also be performed using others techniques [9] and [10] and Michalopoulou [11], where he applied the deconvolution using singular value decomposition and found a better result when used on hyperbolic frequency modulation (HFM). The variance of the estimated TDOA can be calculated and depends on SNR, pulse bandwidth and frequency [12].

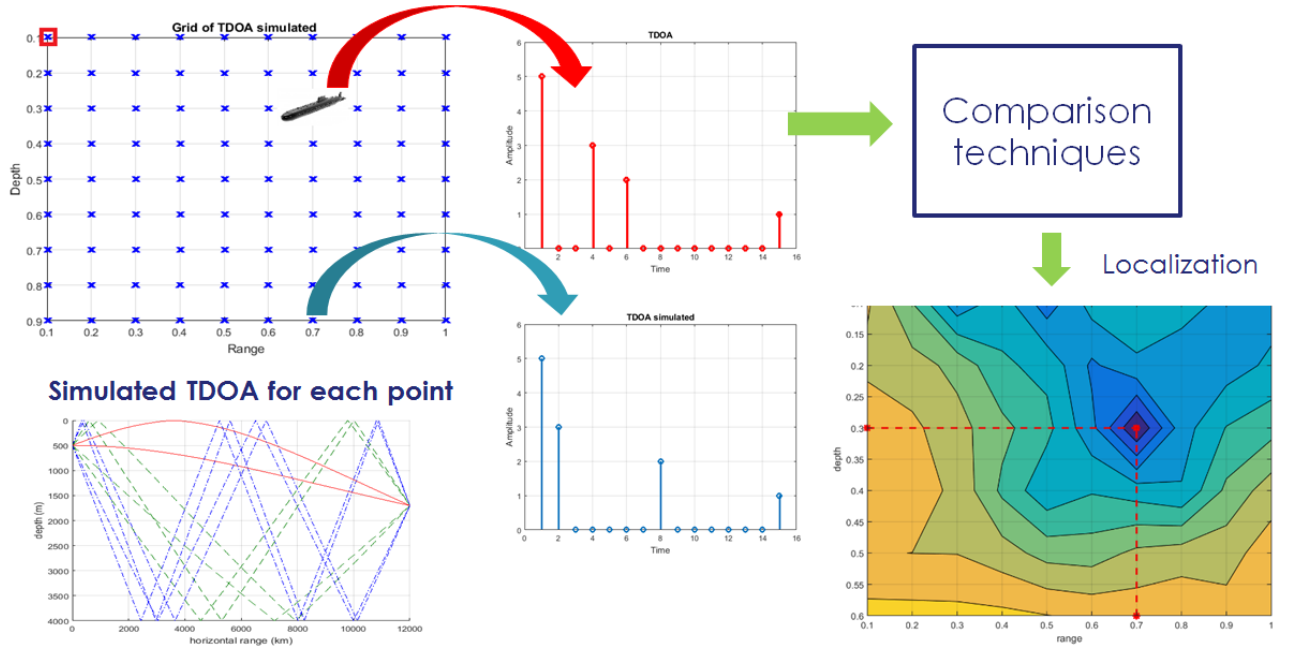


Fig. 1. Final vector of time differences between two datasets

The basic idea consists of first simplifying the problem by reducing one dimension from 3D (azimuth included) to only 2D (range and depth). A cell grid size with variations in depths and range is defined, adopting the Cartesian coordinates with $0 \leq R_x \leq R_{\max}$ and $0 \leq D_y \leq D_{\max}$, where $(R_x, D_y)|s \in S$, is rasterized or pixelated for the x-scale component to an inter-multiple of $1/R_x$ and the y-scale component to an inter-multiple of $1/D_y$, as shown at the Fig. 1 on the left by the x blue, where each of these points is modelled using the ray path propagation. It is well known that by the principle of reciprocity the path from the direction of the receiver to target is the same compared to the reverse way. The next step is extracting the information of the time of arrival and using the Hausdorff distance for finding the possible location of the target. At Fig. 1 on the right, the true location of the target is represented by the red intersection and the estimated location represented by the dark blue area.

The second possible technique applied to localization inversion is process called as model-range signal processing. This technique is used on the project SOSUS. The difference is that now each one of the blue “x-point” at Fig. 1 contains one hydrophone. As the sound propagates though the medium each hydrophone will record the signal with a difference in

time of arrival (range-only measurement or trilateration). By using these time differences applied on the network is possible to estimate the location of the target. The third technique is using an array instead of only one hydrophone in all blue “x-point”. Now by using the beamforming is possible to extract the information of the angle of arrival (bearing-only measurement or triangulation), thus with only two correctly separated arrays is possible to estimate the target location. The disadvantage of having to use a higher number of hydrophones which have to be connected as a network is its high cost.

The most important liability to an accurate inverse localization is the sensitivity to a significant data-model mismatch, especially in shallow water. Incompatibility (mismatch) will always exist on real configuration especially when the environment is modeled as range-independent environments. In this case, the ocean-acoustic environment is considered as horizontally stratified, meaning that there is no variation of the input parameters with the range, only with the depth for the SSP. However it is well known that there is always some degree of variability in the ocean parameters such as: the SSP, the geo-acoustics of the seabed, the bathymetry, among others. The next possible source of mismatch is generated by human error and for malfunctioning of equipment, such as sensors that are not calibrated or positioned accurately, connections not working properly, among others.

1.3. Simulation program

In 2009 Etter [3] reviewed the ocean acoustic models, where according to him comprises 126 propagation models, 19 noise models, 26 reverberation models and 34 sonar-performance models. From the total about 18% is designed to shallow water.

Accurate modeling and prediction of the acoustic environment is essential to an understanding sonar performance in coastal oceans. However, locating targets in an operational context cannot rely on too complex time-consuming propagation models, referred as Research Models, characterized by high accuracy and high sensitivity to environmental variations. For remaining close to practical situations, the representation of the shallow water medium involved in our localization scheme, was deliberately highly simplified using a range-independent acoustic propagation model, and for a nominal flat seafloor with a local averaged depth. This simplifications result in a reduced time-consuming and with enough accuracy to permit long-range predictions in a satisfactory way allowing using in an operational situation. According to Etter [5], an acoustic model is called physical or analytical when it represents the theoretical conceptualization of the physical phenomena that occur in the ocean. Mathematical models include both empirical models, those based on experimental observations, and numerical models, those constructed from the mathematical representation of governing physics. A third type is also defined, the so-called analog models, defined as controlled acoustic experiments in test tanks with the use of appropriate scale factors.

Acoustic models can be classified into three broad categories:

- **Environmental Models** - Environmental models include physics-based or empirical algorithms that are used to quantify the boundary conditions (surface and bottom) and volumetric effects of the ocean environment. Such models include, for example, sound speed, bathymetry, viscosity and chemical relaxation absorption coefficients, surface and bottom reflection loss, and reverberation of the medium due to the presence of bubbles, suspended matter and the biological mass. A further division can be made according its dependence in space dimension starting from 1D, or depth-dependence only (range-independent), 2D (depth and range) and 3D (depth, range and azimuth) both being part of a range-dependent environmental specifications.

- Basic Acoustic Models - In this category are included propagation models and noise.
- Sonar Performance Models – these models are the most complex, since they encompass not only the algorithms of the two previous categories, but also appropriate signal processing models. They are applied in solving specific problems, such as in the detection of submerged objects, mine scanning, among others.

1.3.1 Ray path theory

Ray theory provides a high-frequency asymptotic approximation solution to the wave equation in which the ray paths are independent of frequency. The approximation leads to simple ordinary differential equations in ray coordinates that can be easily solved. The ray method is capable of providing important information on sound propagation without calculating the whole wavefield evolution. Ray theory has an advantage of being computationally efficient and its relationship to geometry makes it simple to follow and understand, however it presents an important disadvantage regarding to the frequency of operation. Ray path cannot be used when the depths are as the same order of magnitude as the wavelength of the received signal due to the approximation of the acoustic wave equations. At low frequency the interference pattern is more stable and due to the leaking phenomenon at frequency close to the cut of frequency the amplitude will be significantly different. Thus, another propagation model must be used to model the environment. Normal modes propagation is more accurate in this situation. On Fig. 2 is presented the range of applicability from the relation of frequency vs depths by the two models.

The asymptotic solution, referred to as the ray series is substituted by the Helmholtz equation and after neglecting higher order terms, two equations are obtained: The Eikonal equation, which evaluates the acoustic energy propagation, and the Transport equation which evaluates the sound intensity at any point. (See Appendix 5)

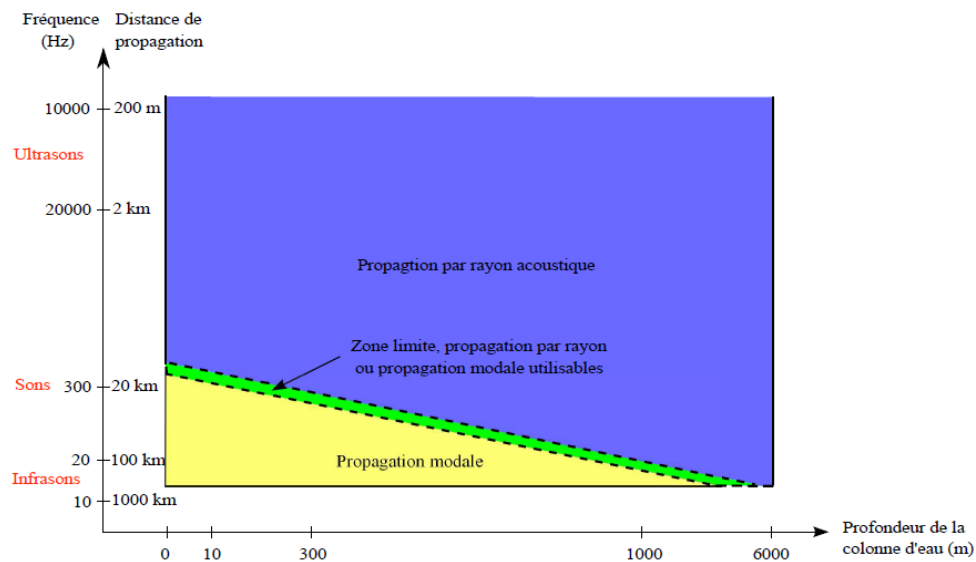


Fig. 2. Final vector of time differences between two datasets reference missing figure

1.4. Sound Speed Profile

The speed of sound propagation in any medium (solid, liquid, or gas) is not constant and it is predicted according to the density and the elasticity of propagation medium, where the density varies with the chemical composition of the water and the elasticity varies with the temperature and pressure. Air bubbles, biological organisms, nutrient-rich coastal regions can also affect the velocity of sound. sound moves more slowly with increasing salinity (1 ppt of salinity at velocity decreases by 1.3 m / s) and and faster when temperature increases (1°C the speed increases by about 4 m / s) and increasing in pressure (each 100 m deep increases by 1.7m/s). An average value for the sound speed, c , is accepted around 1500 m sec⁻¹ in seawater under ambient conditions at a temperature 0°C, 35 ppt salinity and 760 mmHg pressure [13]. The value of sound speed can determined by empirical formula using three parameters, pressure, temperature and salinity which can be measured by sensors dropped on the water. There are number of formulas available to calculate the sound velocity in water given in literature such as [14], [15], [16], [17], [18].

1.4.1 Propagation Loss

As sound propagates through the ocean, the total attenuation in the acoustic channel is calculated by four types of Propagation loss, which contributes to diminish its intensity with range.

- Geometric spreading loss - includes spherical and cylindrical spreading losses in addition to focusing effects.
- Absorption loss - Volume absorption in sea water, caused by viscosity, chemical relaxation and inhomogeneities on the medium. Absorption loss increases with frequency and it is the main reason for transmission in long range being performed by low frequency using sound propagation. High frequency electromagnetic waves and light propagation are absorbed and more sensible to scattering, resulting in a high attenuation within distances of a few hundred meters.
- Reflection loss – Each time that the wavefront touch the boundaries, because of the not so severe mismatch on the impedance of both mediums, a portion of the incident acoustic energy at the bottom may be transmitted into the bottom materials and a portion may be reflected to the medium. For high incident angle, the energy radiated from a source suffers severe reflection loss and will therefore become highly attenuated after just a few bottom bounces. On the other hand, for low incident angle especially to the case of shallow water and long distances, many more bounces are possible. The reflected energy from the bottom eventually returns to the water and combines with the acoustic wave reflected from the first layer. The resultant reflection coefficient from a layered bottom involves both a loss in amplitude and a change in phase relative to the incident wave.
- Scattering loss - A rough sea surface or sea floor causes scattering of the incident sound. The result is a decay of the mean acoustic field in the water column as a function of range (scattering loss), with the scattered energy being lost to the ocean bottom through steep-angle propagation. The scattering loss increases with increasing frequency,

1.4.2 Geometric spreading loss

The geometric spreading loss is a local loss of power that occurs in the propagation of waves due to energy conservation. For close distances, the acoustic wave is modeled by spherical scattering, as the distance traveled by the wave increases, the area of the sphere get bigger, and the consequence is that energy per unit of area gets smaller and smaller. The power loss by spherical scattering is proportional to the square of the distance. For long distance transmissions especially to the case of shallow water due to the boundary interactions, the acoustic wave is changed due to the loss of the spherical symmetry to becoming cylindrical geometry, where the power loss is proportional to distance. In underwater acoustic propagation the geometric scattering falls between the spherical and cylindrical geometry. The geometric spreading is not dependent of the frequency.

1.4.3 Absorption loss

When sound propagates in the ocean part of the acoustic energy is continuously absorbed. This energy is then converted into heat due to the relative motion between water particles. It takes a finite time for a fluid to respond to a pressure change due to its compression and rarefaction effects caused by an acoustic wave, or to relax back to its former state after the pressure has returned to normal. This process is called relaxation. Chemical relaxation, which occurs in sea-water, involves ionic dissociation that is alternately activated and deactivated by sound compression and rarefactions. In sea water, this absorption comes from the molecular chemical relaxation process, which involves two different molecules depending of the frequency: the first, Magnesium Sulphate (MgSO_4) molecules contributes to absorption loss below 200kHz, and a Borid Acid (B(OH)_3) molecules contributes to absorption loss for frequencies below 2kHz as shown at Fig. 3. The second problem, which contributes to decay the intensity with range is the scattering effects by different kinds of in homogeneities present in the medium.

Along various models to calculate the final attenuation, the Model of Francois and Garrison claims to have a better accuracy, Appendix 5. The input parameters to its equations depend on the seawater properties, such as temperature, salinity, and pH as well as the frequency of the sound and depth.

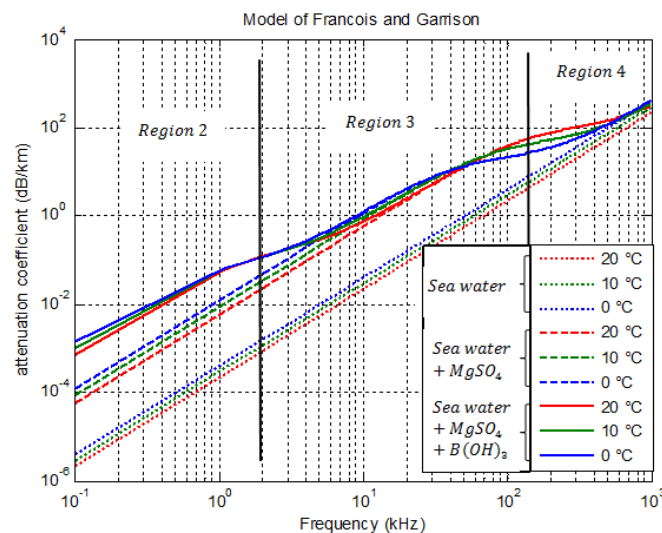


Fig. 3. Model of The Francois and Garrison

The absorption coefficients are: salinity of 35 ppt, PH of 8.0, and a depth of about 0 m. The temperature was varying from 0 10 and 20 graus.

The absorption loss is also responsible for finding the optimal frequency in a propagation medium. At lower frequencies with increasing wavelength the efficiency of the duct to confine sound decreases (the cutoff phenomenon). Leakage out of ducts in low frequency usually less than 100 Hz increases the penetration of sound into a seabed increasing the attenuation. In the high-frequency as shown at figure x, there is a relevant increasing of the attenuation of the sound. Thus, high attenuation is finding at both high and low frequencies, while intermediate frequencies have the lowest attenuation thus achieving long distances. Typically, the optimum frequency is in the range 200–800Hz for a water depth of 100 m. [19]

1.4.4 Bottom Loss

Seabed sediments can be modeled as a fluid, which means that they support only one type of sound wave - the compressional wave (type P). This is usually a good approximation since that the sediment is often considerably less than of a solid, because otherwise, the medium must be modeled as elastic, including the influence of another type of wave, which is the longitudinal or shear wave (type S).

As said by Jesen [20] a geo-acoustic model is defined as a model of the real seafloor with emphasis on predicted values of those material properties important for the modeling of sound transmission (seabed). The properties of the material must include: The compressional wave speed, the compressional wave attenuation and the density. For elastic medium should also include the shear wave speed and the shear wave attenuation. For an accurate representation of the seabed, the influence with geographical position must also be considered as well as the frequency of the signal, which affects the effective acoustic penetration depth. At high frequencies, details of the bottom composition are required only in the upper few meters or tens of meters of sediment, whereas at very low frequencies (<10Hz) information must be provided on the whole sediment column and on properties of the underlying rocks. [21]

One common classification system developed by the US naval fleet numerical weather center (FNWC) identifies nine bottom classes starting with a low loss sandy at to rock. The layered nature of the bottom sediments causes the complex reflection coefficient to vary with both frequency and angle of incidence. Fig. 4 shows the bottom loss vs the grazing angle for these nine different bottom sediment type at frequency of 1 kHz. **Book reference.**

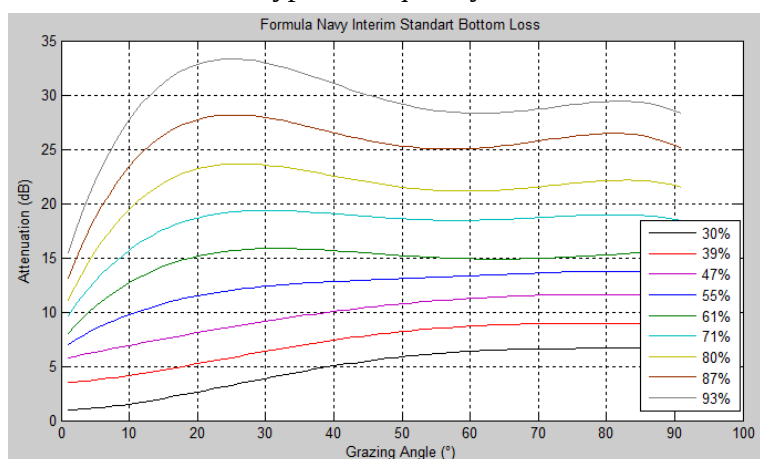


Fig. 4. Final vector of time differences between two datasets

1.4.5 Scattering loss

The scattering is a physic process where the incident wave is reflected after reached a roughness surface adding an additional loss to the specularly reflected (coherent) component resulting from the scattering of energy away from the specular direction. This scattering can causes interference for active sonar systems (process called reverberation). Surface Scattering models have been developed, including scattering due to surface roughness as well as a bubble layer when wave breaking takes place provoked by different winds speeds. [22] If the surface of the sea was flat and smooth, it would be an almost perfect reflector of sound, due to the severe incompatibility of the acoustic impedance at the air-sea interface. Thus, the behavior of this boundary is determined by the roughness and frequency of the acoustic signal. Bottom roughness is also included during the modeling of the propagation channel.

Noise

There are primarily three categories of noise: man-made (anthropogenic), Marine life and ambient noise as shown at Fig. 5. The man-made noise primarily consists of shipping noise, and industrial activities such as offshore rigs and explosions. The Marine life or biologic noise came from animals such as shrimp, whales, dolphins, among others. The last font of noise came from the ambient noise such as wind, waves, water motion, bubbles, precipitation, thermic, earthquake, among others. Those noises are further divide in frequencies by Wenz in his work [26], where he found that the noise level maximum is in the interval 400 - 800 Hz.

The ambient noise for the most part and when all sources are taken together, is a random process, very often stationary with average and mean-square values not varying much with time. The ambient noise, different than the man made noise, comes from all directions though not equally distributed. As said by [23] the noise level in shallow water for the same sea state as for deep oceans is about 5 dB higher. Urick (1983) [22] has shown that in calm winds the level of ambient noise in shallow waters is often lower than in deep waters and that the opposite relationship is observed in the presence of strong winds. Ambient noise can be observed in the frequency range from 20 Hz to 50 kHz. Ambient noise can be observed in the frequency range from 20 Hz to 50 kHz. It is common to divide the broad frequency range into smaller sub-bands, where the intensity levels in these sub-bands take different values and different spectral slopes due to different source mechanisms. One of the main sources of natural ambient sound in frequencies between 100 to 10 kHz is the explosion of bubbles working as an effective sound source. It is created by breaking waves due to the fluctuations in the elevation of the sea surface caused by the wind effects. The effect of bubbles noise is extended to frequencies starting from 20 Hz in shallow areas, having a strong influence overall the total amount of noise (2010). Even in totally calm weather micro sized bubbles in water add up to bigger and bigger bubbles that ascends to the surface, oscillating and generating noise [26]. The next source of noise is precipitation, such as hail, sleet or water droplets. When a raindrop strikes the ocean surface, there is an impact sound of duration several microseconds followed in many cases by the definitive sound of a newly created, shock excited bubble, which penetrates the water surface. All this bubbles effects also contributes to scattering the sound as presented in the previous section. At sea state 1 and below when breaking waves are rare, precipitation is more relevant, contributing to the

increases the noise levels. Ice movements are also a source of noise which at times covers a wide range of frequencies at high level. The minimum noise level for a medium is determined by its thermal agitation effects.

Shipping noise or radiated noise can be grouped under three major classes: cavitation by the propeller, vibrations from on-board machinery and hydrodynamic effects such as turbulence, resulting from the irregular flow passing through the moving vehicle. Propulsion systems are the most dominant part. The noise generated from ships is grouped in three frequency bands: low (1-10 Hz), intermediate (10-500 Hz) and high (500 Hz - 20 kHz) frequencies [26]. Ships generate sound below 50 Hz that emanates from the propeller and the hull.

Animals are known to produce sound to communicate, orient and to hunt. The sounds have a wide variety of distinctive types such as: cries, barks, grunts, mewings, chirps, whistles, taps, cracklings, clicks, etc. Biological noise varies with time, location and frequency and is an important part of the ambient noise.

The general spatial distribution of the ambient noise, including its coherence properties, can be used to reduce its effect of the received signal, extracting a signal embedded in noise.

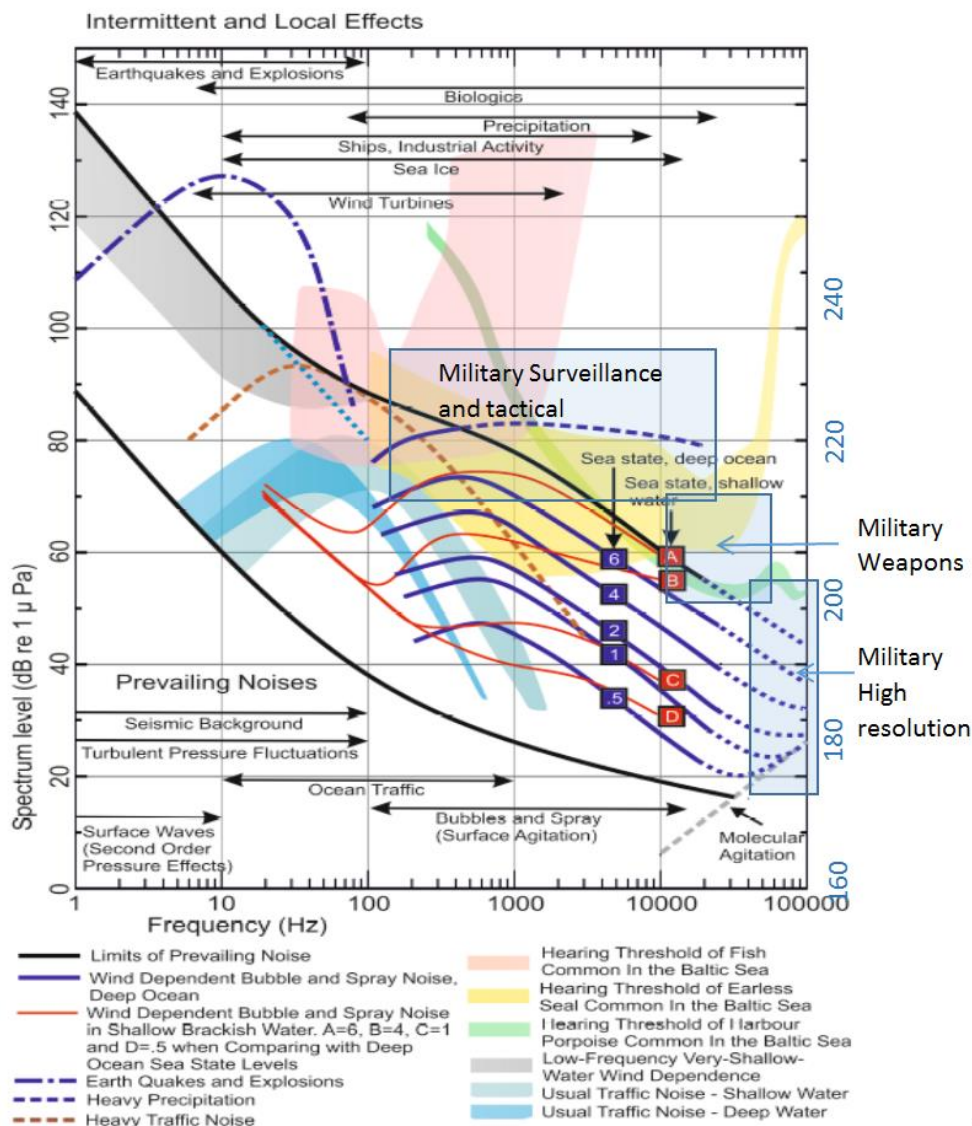


Fig. 5. Noise distribution.

1.5. Chapter Summary

The first section of this chapter presents the complex behavior and peculiarities of the sound propagation in shallow water, which features many interactions with complex boundaries (rough seabed, rough moving sea surface). The process used to perform the localization inversion is presented as well as the comparison with other techniques on the literature. The basis for the ray path propagation is explained and its equations can be found on appendix. The propagation loss and the noise are presented which contributes to reduce the performance of the inverse localization. The propagation loss is divided in four groups: Geometric spreading loss, Absorption loss, Reflection loss and Scattering loss. Each group is then further analyzed. The noise is divided in three groups: man-made (anthropogenic), Marine life and ambient noise. Each group is detailed and separated by its frequency and level of noise. The concept of SSP is presented as well as its main equations.

CHAPTER 2

Bibliography Survey of inversion techniques

Contents

2.1. Introduction	16
2.2. Historical survey presented at the literature	17
2.3. Definition	19
2.3.1 Green's function	22
2.3.2 Covariance matrix estimation	23
2.4. Matched field signal processors.....	24
2.4.1 Bartlett (conventional) MFP processor.....	24
2.4.2 MVDR-MFP processor	25
2.5. Matched field tomography - MFT	25
2.6. Chapter Summary	26

2.1. Introduction

Matched field processing (MFP) is an underwater acoustic sonar array signal processing method widely used to estimate an unknown parameter from the array of measurements based on ocean physical propagation mode. The knowledge of the complex ocean environment, array configuration and the noise field is incorporated into the signal processing algorithms. The use of MFP is divided in two applications: the first application is to localize an underwater source (detect, localize and track), used in naval surveillance and marine monitoring. It is mostly common defined by depth and range in a 2D scenario, and most recently considering a 3D propagation model, it is also able to estimate the azimuth [24]. The second application is geoacoustic inversion, where the MFP is used to estimate the ocean environmental parameters, such as: sound speed profiles, water temperature, salinity, bathymetry, density and elasticity of the seafloor of the ocean waveguide, etc. It is, also referred as Matched field tomography (MFT).

The MFP works based on matching/correlate the acoustic pressure field measured at an array of spatially distributed sensors with modeled replica fields computed for the acoustic waveguide. The MFP can be performed considering only one hydrophone or, mostly used, an array of hydrophone (linear array, either vertical VLA or horizontal HLA, nevertheless can be applied to other geometries arrays, cylindrical or spherical arrays). It is mainly apply in a passive array sonar system, however can be also used in an active array sonar system. It is

derived from the wave equation, via a numerical sound propagation model, either considering range dependent or independent (such as the normal mode model, the parabolic equation, and the ray path propagation, etc.), over a grid of points, usually 2D in range and in depth, of all possible source positions in the observation sea area, however can also be used in 3D configuration, used in the case of high azimuthally-dissymmetric environment (high variation of the bottom column depth where can introduce Eigen paths from different azimuth).

The resulting output of the MFP cost function produces a likelihood surface that shows peaks corresponding to the estimated range and depth of the source (maximum peak value over a grid, which is maximized when the modeled field is similar to the measured field). This value corresponds to the best match between the two sets, measured and modeled, which should indicate, considering an accurate propagation model, the true source position. This surface is called as ambiguity surface and may also contains peaks at ambiguous ranges and depths, which can introduce some mismatch at the source position, making it hard to distinguish the source from the sidelobes. A better understanding of the real ocean environment and its variability, e.g. internal waves, ocean fronts, bathymetry and the geoacoustics of the seabed, recorded by better performance instrumentation, results in a better localization accuracy.

2.2. Historical survey presented at the literature

Several concepts in ocean acoustics were developed at the same time and they have important contributions which favored the development of the work on MFP. Essentially, MFP is a generalization of the conventional linear plane-wave beamforming method (PWB). The work on PWB starts from the beginning of World War II, used to detect the azimuthal direction of the source, and it remains in used in innumerable applications nowadays. However, PWB, considering only an isolated array, has a significant limitation as it is not possible to directly determine the depth and range of the source. The way to overcome this limitation is done by picking the target direction (azimuth) as a function of time, adopting no variation on the target motion, a process called as target motion of analysis (TMA), being the first solution to underwater localization [25]. The second solution consists of multiple sensors in different sites locations using PWB to estimate the azimuth of the source. The localization is then performed by find the position of the interconnection of the bearing measurements for different locations, method called as triangulation. Using this method, it was created in 1949 the project SOSUS (**SO**und **SUR**veillance **S**ystem) with the goal of localizing soviet submarines. The limitation of PWB is that it does not consider the complex ocean environment information, which are inappropriate for processing a real underwater environment (2D localization: range and depth), especially at low frequency and long source range (with the variation of the sound speed profile in depth and boundaries conditions on the ocean waveguide [26]). A new method must be created, where those complex information, defined by the medium, are modeled using an acoustic propagation model (ray path, normal modes, etc.). This modeled information is then used as a reference/base for the comparison with the measured signal to the localization problem. This process is known as model-based processing.

The history of MFP starts back on 1966, where Clay [27] was the first to model the underwater medium using normal modes propagation, and at the same time he also identified the importance of the waveguide effects, arrays and signal processing on this process. Later, in 1972 Hinich [28], using maximum likelihood equations, theoretically approached source localization with vertical line array. In 1976, Carter [29], using free space models, investigated the propagation considering a wavefront curvature. In 1976, using the work of

these three pioneers, Bucker [30], who is credited to be the first to formulate the conventional MFP or Bartlett MFP, now for the first time used realistic shallow water environmental models with complex bottom reflections. He also have shown that the comparison based on the magnitude squared of the correlation between the modeled and the measured signals resulting what is known as ambiguity surface, have enough resolution to allow the inversion, which represents localization in range and depth [31]. Next In 1980 and 1981, The Bucker's concept were adapted by Klemm [32] addressing for the first time the use adaptive processing with what he called "Approximate Orthogonal Projection.", during his experiments he considered stationary and non-stationary environment, and he found out that the he could have a better performance using the Maximal entropy approach, however this end ups with complex sidelobes problems, especially at low Signal to Noise Ratios (SNR). Later in 1987 and 1988, Fizell [33] and Baggeroer [34] used different variations of the high-resolution or adaptative beamformer. Overall the high-resolution beamformer, the one that so far presents good performance is the Capon's minimum variance distortionless response (MVDR) [35].

In 1985, many different works on MFP starting to appear, Shang [36] noticed that each position in range and depth is associated with particular modal coefficients, and he could use that information to localize the source using the "mode filter", a method called as matched mode processing (MMP), the only limitation is that the number of hydrophones must be greater than the number of modes (which is generally the case of shallow water and low frequency). The MMP presents a better robustness to some environmental mismatch allowing mismatched modes to be removed. However, if the numbers of modes are not enough due to a low frequency and shallow water, this can leads to degradation of the source location introducing a high sidelobes ambiguity resulting in a biased estimation [37]. On the same year, Tappert [38] investigated a variant of the MFP called as back-propagation method, where he uses the phase conjugation in back-propagation to reverse the waveguide dispersion, Instead of correlating the field with a model replica used in MFP. In 1994, Voltz and Lu [39] addressed back-propagation method in the time domain using ray path theory. In 1985, Ozard [40] and 1986, Schmidt [41] exploited the Subspace-based signal analysis using singular value decomposition (SVD), based to MUSIC algorithm, which exploits the fact that the actual steering vector (Green's function) is orthogonal to noise subspace. The music requires some assumptions described in [42]. In 2000, Jesus [43] investigated this method to localize a source using a single hydrophone configuration. Another variant of the MFP was introduced in 1988 by Baggeroer [44] and [45] named as multiple constrain matched field processor (MCM). The MCM is an improvement of MVDR, it presents the best of both processors: From the Bartlett MFP, the wide mainlobe which correspond to a better tolerance under certain deterministic environmental mismatch with a small spatial resolution, and from the MVDR the reduction of sidelobes effects, at the same time it is more sensible when the SNR is low.

The use of experimental data started in 1985, Fizell and Wales [46] demonstrated the use of MFP and later, in 1989 Hinich and Sullivan [47], demonstrated the use of MMP, and compared with the Bucker's processor.

All the assumptions given in these methods so far, consider that the acoustic pressure field is calculated by deterministic wave equations and it is time invariant. However, a deterministic treatment of the medium is not the most adequate, since the medium is in constant uncontrolled and unknown variation of its parameters, and then a stochastic approach may be a more appropriate approach to determine realistic wave propagation [48]. In 1991, Richardson and Nolte [49], exploited the use of an explicitly Bayesian formulation of the problem as an alternative to the mismatch problem. They characterized the ambiguity surface by its posteriori probability density function (PDF) of the source position related with the

signal and environmental parameters. The MFP with posterior probability constraints (MFP-PPC) presents the advantage of robustness to the environmental mismatch. For more [50]

In 1992 Westwood [51] and in 1993 Brienzo [52] addressed the use of Broadband (or multifrequency) MFP. The coherent combination in frequency at the ambiguity surfaces shows better performance than incoherent combination especially when the environment mismatch and ambient noise level are significant. A matched-phase coherent processor was then proposed to compensate these phase shifts. [53]

In 1991, Collins [54] exploited the concept of Focalization, where he treats the environment as an acoustic lens searching for the best focalized value. The ocean-acoustic parameters recursively suffer small alterations (parameter optimization method), and a search is performed on the ambiguity surface, resulted from the MFP processors, for the value which minimize the cost function (maximal resemblance), over all unknown or partially unknown parameters. High resolution cost functions have the capability of suppressing ambiguous solutions. In 1991 and 1992, Lynch [55] and Collins [56], using the concept of focalization applied to a known source location, used as reference, they exploited the variations of the different parameters, search for the ones which would give the correct know location, a process called Geo-acoustic inversion.

In 1989, Fink introduced the concept of Time Reversal TR, since then it has been used in many areas, telecommunications, medicine, though-wall motion detection, etc. it was applied for underwater localization in 2015 by Yu [57]. TR relies on the property that the wave propagation is unchanged considering a small time interval, being in this sense invariant [58]. The signal emitted from a source and subsequently received by a transceiver is time reversed and retransmitted into the medium by the array, this process tent to focus automatically on the source, either in time and space, given a gain of more than 20 dB, allowing localizing targets obscured by noise or in rich scattering environments, due to the high energy loss. [57]

In 2000, Michalopoulou [59] introduced the concept of matched impulse response processing which is a Model-based matched filtering (MBMF), to perform the localization inversion with better performance than the incoherent MFP. The main difference compared with the MFP is that includes the temporal structure of the acoustic field using time-series matching for inversion. Therefore MBMF is both temporally and spatially coherent while conventional incoherent broadband MFP is spatially coherent only. This temporal coherence leads to improved inversion results and reduced sidelobes effects. The disadvantage is that it can only be used in a cooperative source system (when the source signature is known). One possible way to overcome this limitation is to isolate the high intensity path from the beamforming processing to estimate the source signature.

In 2009 Bahr [60] presented the use of trilateration or range-only measurements, process similar to the GPS system to make navigation for Autonomous Underwater Vehicles (AUVs).

In 2017, Niu [61] presented the use of supervised machine learning applied on underwater target localization, and in 2018, Huang [62], used deep neural networks to localize a source in a shallow water enviroment.

2.3. Definition

On the previous section the historical survey of the MFP was presented. Here will be investigated the comparison between different processors, inspected from the context of:

resolution of the mainbeam width, sidelobe level, sensitivity to the environment mismatch (mostly due to the inexact knowledge of the sound speed profile and the boundary conditions) and the relation with low signal-to-noise ratio (SNR). Here will also be described the main problems of MFP and will be exploited the steps of the model based processing using MFP and the two most common MFP processors.

MFP is mainly divided into two categories:

- The conventional MFP or Bartlett MFP, which produces a relatively broad main lobe, been more robust to the model mismatch with the disadvantage of presents low spatial resolution on its ambiguity surface, and with high sidelobe levels on the ambiguity surface, which are often indistinguishable from the mainlobe. And the adaptive matched field processor (AMFP). There are several processors in this category, the most common are: the Minimum Variance Distortionless Response (MVDR), which is a high-resolution method with a narrow mainlobe, which results on high spatial resolution on its ambiguity surface, however it has an intrinsic defect of poor robustness, been extremely more sensible in presence of environmental mismatch. The MVDR also presents a reduction of the sidelobe levels even in a low-SNR circumstance, reducing ambiguity point locations, which may leads to a bias location. It passes signal with no distortion from the specific direction while adaptive suppressing noise from other locations by null placement and “estimator-subtractor” processing. And the second algorithm is the Multiple Constraint Method (MCM) is an improvement of MVDR with better tolerance for deterministic environmental mismatch adding multiple linear constraints to the weight vector, which control the sharpness of the mainlobe. Large mainlobe is more robust against environmental mismatches however with a lower spatial resolution, and vice-versa. There still have many other high-resolution method which will not be described here but it was presented at the previous section.

Although the MFP is the most accurate technique to localization, it still presents serious challenges seen as disadvantages to its applicability:

- The accuracy of the MFP is directly related with the cell grid size (resolution of the ambiguity surface). The localization will often fail if the target is located at the middle of the cell grid with a low spatial resolution (high value of the step grid).
- And the most important limitation of the MFP, the inevitable inaccurate knowledge about the acoustic environment information, especially in shallow water environment, restricting the application of MFP by decreasing largely its performances. This phenomenon is well-known as environmental mismatch. The principal parameters which can induce errors at the localization include: sound speed profile, water column depth, geo-acoustics seabed parameters, internal waves, surface condition (surface roughness from wind and waves), and hydrophone positions (vertical and horizontal position and arrays tilts). [63] [64] [65] [66] [67]. These sensitivities can occur around the mainlobe peak, referred as local errors, or around the sidelobe peaks, referred as outliers. It is therefore simple to associate that the accuracy of propagation models in ocean acoustics increases dramatically by using more precise equipment to reducing those mismatches, resulting in a better performance of the localization.

A flow diagram of MFP is given on Fig. 6. It presents three main components, which will be individually described in the next subsections:

- Sample covariance matrix estimation (red color): The covariance $\mathbf{S}_{xx}$, is obtained from the measured source signal and it is going to be used as the reference of the source position to the correlator. Usually, this is done by a sum of outer products on the snapshots of the ambient field.
- Green's function (green color): In conventional array signal processing plane wave beamforming algorithms, the phase of the signals is controlled by the steering vector, generating the beam pattern of the array [68]. In a case of MFP this steering vector is replaced by the Green's function $\mathbf{G}(\mathbf{w}_0, \mathbf{P})$ which in this case is defined by the impulse response of an inhomogeneous sound wave equation, computed using the propagation model which considers the environmental information of the medium. The notation $\mathbf{P}$ includes both the possible source location and unknown environmental parameters, which are in many cases a priori estimated over the interested sea area of the experiment.
- Matched field algorithm (blue color): It is a cost-function of the sample covariance matrix $\mathbf{S}$ correlated with the Green's function $\mathbf{G}(\mathbf{w}_0, \mathbf{P})$, which generate the ambiguity surface. Note that the information of the time of arrival (TOA), angle of arrival (AOA), and amplitude of arrival, can be extracted from both, the covariance matrix and the Green's function. The maximum of the ambiguity surface gives the most likely position of the sound source in range and depth (2D scenario). From the several MFP algorithms only two will be described here in the following: the Bartlett MFP and the Capon's MVDR. Those algorithms are the basis for the most widely used localization inversion.

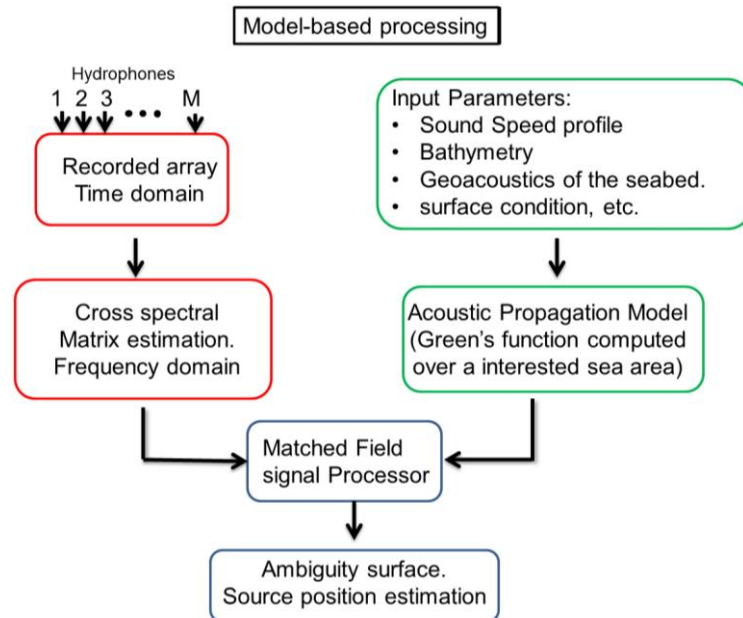


Fig. 6. MFP flow diagram.

2.3.1 Green's function

The Green's function has the information of the modeled signal pressure field for each position in the observed area, and represents the basis for the correlation used in MFP. The modeled signal pressure field is simulated using a propagation model (Ray path, normal mode, etc.) based on the physical ocean waveguide parameters, (either for deep water or shallow water scenario), frequency range (low frequency or high frequency range), and number of hydrophones (single hydrophone configuration or an array of hydrophones).

The received acoustic signal is given, in time domain, by:

$$\mathbf{y}_{m,n}(\mathbf{t}, r_i, z_j) = \mathbf{v}_{m,n}(\mathbf{t}, r_i, z_j) * \mathbf{x}(\mathbf{t}) + \epsilon_{m,n}(\mathbf{t}) \quad m = 1, 2, 3, \dots M$$

Where:

$\mathbf{v}_{m,n}(\mathbf{t}, r_i, z_j)$ is the impulse response of the medium at a specific location r_i, z_j for each hydrophone m , and for the time snapshot index n discretized in time.

$\mathbf{x}(\mathbf{t})$ is the source transmitted waveform, which in case of a non-cooperative case will be unknown. And;

$\epsilon_{m,n}(\mathbf{t})$ is the noise, assumed spatially and temporally white, zero-mean and uncorrelated with the transmitted signal.

The symbol $(*)$ stands for convolution, t = time, r = location in range, z location variable in depth

The impulse response of the medium is then transformed using the Fast Fourier Transform to the frequency domain, given by:

$$v(w, r_1, z_1, P) = \int_0^T \mathbf{v}_{m,n}(\mathbf{t}, r_i, z_j) e^{-j\omega t} dt \quad m = 1, 2, 3, \dots M$$

We assume that the solutions to the wave equation at the array locations, with M number of hydrophones, $\mathbf{v}(\mathbf{w}, r_i, z_j, \mathbf{P})$, are incorporated into a signal matrix $\mathbf{v}(\mathbf{w}, \mathbf{r}, \mathbf{z}, \mathbf{P})$ where $\mathbf{P}$ denotes parametric dependencies upon source location and environmental parameters used at the propagation model. For sound propagation numerical calculations in a range-independent environment, the value of $\mathbf{P}$ will be constant in range and to simplify the equation it can be removed. The final matrix is then associated with each frequency w , where in case of the broadband transmitted signal, either coherent or incoherent average will be performed by the MFP.

$$\mathbf{v}(\mathbf{w}, \mathbf{r}, \mathbf{z}, \mathbf{P}) = \begin{bmatrix} v(w, r_1, z_1, P) & v(w, r_1, z_2, P) & \dots & v(w, r_1, z_j, P) \\ v(w, r_2, z_1, P) & v(w, r_2, z_2, P) & \dots & v(w, r_2, z_j, P) \\ \dots & \dots & \dots & \dots \\ v(w, r_i, z_1, P) & v(w, r_i, z_2, P) & \dots & v(w, r_i, z_j, P) \end{bmatrix}$$

Where in each possible position r_i, z_j in the previous matrix $\mathbf{v}(\mathbf{w}, r_i, z_j, \mathbf{P})$, considering only 2D variation, range and depths, is performed for M number of hydrophones.

$$v(w, r_i, z_j, P) = \begin{bmatrix} v_1(w, r_i, z_j, P) \\ v_2(w, r_i, z_j, P) \\ \dots \\ v_M(w, r_i, z_j, P) \end{bmatrix}$$

2.3.2 Covariance matrix estimation

The cross spectral density matrix (CSDM) or covariance matrix is a fundamental element of MFP. It is performed through estimation of the cross-spectral functions of the signal at the output of the sonar array. It is essentially a coherent summation of the weighted received acoustic field at spatially separated hydrophones for each single frequency. The cross-spectral function may be defined with a Fourier transform of the cross-correlation function or directly via finite Fourier transform of the input time domain signal. Therefore it captures the spatial coherence of the acoustic field in the ocean.

$$R_m(w) = \int_0^T r_m(t) e^{-j\omega t} dt \quad 0 \leq t \leq T \quad m = 1, 2, 3, \dots M$$

The received signal can also be segmented into snapshots and harmonically decomposed using an FFT as a tentative to reducing the influence of the sidelobes. The snapshots may be windowed and overlapped as often done in Fourier transform based methods of spectrum estimation [31]. These snapshots are given by:

$$R_{m,i}^l(w) = \int_{T_l}^{T_l+T_w} r_{m,i}(t) a(t - T_l) e^{-j\omega t} dt \quad 0 \leq t \leq T \quad m = 1, 2, 3, \dots M$$

Where:

$\mathbf{r}_i(\mathbf{t})$, is the signal recorded waveform from the array position of M hydrophone at each i-index snapshots,

$a(t)$, is the window, normally rectangular function applied to the received signal to control sidelobes,

$\mathbf{T}_l$, is the start of the lth segment of data,

$\mathbf{T}_w$, is the duration of the window function.

The cross-spectral function of the two processes is defined:

$$S_{xx} = \frac{1}{L} \sum_{l=1}^L R_m(w) R_m^H(w)$$

Where :

L is the number of snapshots and R is the complex envelope of the received signal at the array elements; and

$\mathbf{S}_{xx}$ represents the sample covariance matrix of the received signal emitted from the actual source location A with background noise, it is the correlation of the received signal at the hydrophone M with all the others hydrophones.

In order to be used on the MFP algorithm the same matrix formulation regarded with the Green's function will be adopt, considering a Broadband signal and a received array:

$$R_m(w) = \begin{bmatrix} R_1(w_1) & R_1(w_2) & \dots & R_1(w_N) \\ R_2(w_1) & R_2(w_2) & \dots & R_2(w_N) \\ \dots & \dots & \dots & \dots \\ R_M(w_1) & R_M(w_2) & \dots & R_M(w_N) \end{bmatrix}$$

The row represents the frequency spectrum of the signal recorded waveform and the column represents the position of the M hydrophones. The array cross-spectral matrix for the n-th frequency bin is:

$$S_{xx}(w) = \begin{bmatrix} R_1(w_n)R_1^H(w_n) & R_1(w_n)R_2^H(w_n) & \dots & R_1(w_n)R_M^H(w_n) \\ R_2(w_n)R_1^H(w_n) & R_2(w_n)R_2^H(w_n) & \dots & R_2(w_n)R_M^H(w_n) \\ \dots & \dots & \dots & \dots \\ R_M(w_n)R_1^H(w_n) & R_M(w_n)R_2^H(w_n) & \dots & R_M(w_n)R_M^H(w_n) \end{bmatrix}$$

The symbol (H) stands for the complex conjugate operator or the Hermitian matrix. The cross-spectral matrix for an M element array is square MxM matrix for a given frequency ω_n .

2.4. Matched field signal processors

Two matched field processors are subject to investigation in this thesis. The first one is the classical or Bartlett matched field processor and the second one is the so called minimum variance distortion less processor (MVDR).

2.4.1 Bartlett (conventional) MFP processor

The most known method in MFP is the conventional MFP also referred as linear Bartlett MFP due to its simplicity and its robustness against mismatch between estimated and real parameters, being a reference for all the others more sophisticated adaptive processors. The Bartlett MFP weights the measured data by a normalized version of the Green's function and a normalized version of CSDM. For data received at L hydrophones, the ambiguity surface $\mathbf{P}_{Bart}(\mathbf{w}, \mathbf{r}, \mathbf{z})$ can be expressed in a quadratic form in terms of the sample covariance matrix $\mathbf{S}_{xx}(\mathbf{w})$ and the Green's function. This estimator calculates in the frequency domain an inner product between pressure field measured (normalized CSDM - $\mathbf{S}_{xx}(\mathbf{w})$) and replica pressure fields modeled (normalized Green's function $\mathbf{v}^H(\mathbf{w}, \mathbf{r}, \mathbf{z})$), which was calculated for probable values of the unknown true environmental parameters. The Bartlett estimator is coherent in space and incoherent over frequency [69] .

$$P_{Bart}(w, r, z) = v^H(w, r, z)S_{xx}(w)v(w, r, z)$$

A global search is then performed on the ambiguity surface $\mathbf{P}_{\text{Bart}}(\mathbf{w}, \mathbf{r}, \mathbf{z})$, and the maximum peak value, which represents the closest similarity between the modeled and measured field, gives the most likely position of the source. When the noise is spatially homogeneous, the output of this beamformer has the highest possible SNR [26]. The performance of the Bartlett MFP can be improved by simply incoherent averaging the ambiguity surface over frequency, because it tends to reinforce the main peak at the true source location while reducing the sidelobes. However a better performance is obtained by a coherent averaging over frequency [70] and [71].

2.4.2 MVDR-MFP processor

MVDR method is a classic adaptive algorithm for MFP, derived with quadratic constraints [68], characterized by its high resolution and high sensitivity to environmental mismatch. It has been proven to be one of the more robust of the adaptive array algorithms for MFP [72] for more [31]. It is often misleadingly referred to as the "maximum likelihood" method [26], however it does not perform maximum likelihood parameter estimation. The algorithm attempts to reject interfering sources while maintaining unit gain and zero phase shift for each look direction minimizing the variance at the output of a linear weighting, $\mathbf{W}_{\text{MVDR}}^H(\mathbf{w}, \mathbf{r}, \mathbf{z})$ of the sensors subject to the distortionless constraint. MVDR processor requires accurate replica signals which are especially true for MFP since it is the detailed spatial structure of the replica that determines the invertibility in the parameter ambiguity plane. The optimum weight of MPDR (similar to the minimum variance steering vector) can be solved as:

$$\mathbf{W}_{\text{MVDR}}^H(\mathbf{w}, \mathbf{r}, \mathbf{z}) = \frac{\mathbf{v}^H(\mathbf{w}, \mathbf{r}, \mathbf{z}) \mathbf{S}_{xx}^{-1}(\mathbf{w})}{\mathbf{v}^H(\mathbf{w}, \mathbf{r}, \mathbf{z}) \mathbf{S}_{xx}^{-1}(\mathbf{w}) \mathbf{v}(\mathbf{w}, \mathbf{r}, \mathbf{z})}$$

The constraint of no distortion implies that the optimal filter frequency response $\mathbf{W}_{\text{MVDR}}^H(\mathbf{w}, \mathbf{r}, \mathbf{z})$ multiply in frequency domain by the impulse response of the medium $\mathbf{v}(\mathbf{w}, \mathbf{r}, \mathbf{z})$ is equal to 1 (unity gain). As a result it is possible to receive the input signal at the output of the processor without distortion. Minimization of the mean square of the output noise leads to MVDR beamformer first derived by Capon. [73]

Usually the covariance matrix is formed from enough data vector that it is invertible. The MVDR ambiguity surface is calculated by:

$$P_{\text{MVDR}}(\mathbf{w}, \mathbf{r}, \mathbf{z}) = [\mathbf{v}^H(\mathbf{w}, \mathbf{r}, \mathbf{z}) \mathbf{S}_{xx}^{-1}(\mathbf{w}) \mathbf{v}(\mathbf{w}, \mathbf{r}, \mathbf{z})]^{-1}$$

2.5. Matched field tomography - MFT

Initially MFP was created to solve the source localization problem, however it was realized that it could not only estimate the position of the source but also infer properties of the propagation medium applying some form of inverse theory. This process is nowadays

referred to as matched field tomography (MFT). It is considered an extension of MFP. In most applications there are inevitably some uncertainties in the physical parameters of the ocean model, which means that the ocean is too variable in both space and time for them to provide an accurate environmental model needed for source localization applications especially using high resolution algorithm. In addition, these quantities may be range dependent and require the appropriate propagation codes. It seems clear that having a better estimation of these parameters will result to a better resolution and fewer ambiguities solutions. Environmental parameters may include: sound speed profile, geoacoustic properties of the bottom, surface roughness, inhomogeneities in the ocean such as internal waves, local bottom anomalies and/or surface realization, etc. The MFT can also be used to identify which parameters has strongest/ weakest influence over the measured signals.

The MFT works by using wideband sources at known locations, adopting a stochastic approach (small variations of the parameters) and looking for the best value of the ambiguity surface associated with the best value of the parameters variations. The technique described at the historical section called as focalization, whereby the environmental model is adjusted to optimize a cost function for the error in the predicted replica [56], is now adapt to the situation when the source and the receiver geometry and position is known, and used to find the best value of the parameters.

2.6. Chapter Summary

The base of this chapter is Matched field processing (MFP) methods, which are used to two different areas of study: firstly introduced to source localization, and later extended to estimate the geoacoustic ocean environmental parameters. *Matched-field processing is a method for exploiting the effect of the ocean environment on the acoustic pressure field in order to estimate a source location.* The accuracy of the localization is direct affect by the knowledge of the ocean environment, being a limiting factor for localization. This limitation is more robust in shallow water due to complex boundaries interactions (surface and bottom)

The Historical survey was presented in the first section of this chapter and includes the mostly used methods to localization inversion. The most robust of them consists of using some sort of simulation of the channel as a base to the comparison called as model-based processing and includes: Matched field processing (MFP) divided in two groups: the first group, the conventional MFP or Bartlett MFP; and the second group adaptive or high – resolution algorithms: the Capon's minimum variance distortionless response MVDR, the multiple constrain matched field processor (MCM) and MUSIC algorithm. The localization can also be performed using matched mode processing (MMP). In sequence was presented the concept of focalization and posterior probability constraints both used to improve the accuracy of the localization. The last concept has the propose of geo-acoustic inversion, named as Matched field tomography (MFT). The other method to localization inversion which also uses model-based processing is the backpropagation approach. The two first approaches created to localization inversion which does not uses model-based processing was the target motion analysis (TMA) and the triangulation with receiver in different location responsible for the spatial diversity. Both methods rely on the beamforming techniques to find the azimuthal direction of the source transmitted waveform. Some recent works on triangulation considering the implementation as a model-based processing using MFP, which in many situations will increase the performance of the localization.

The second subsection of this chapter describes the comparison between different processors, regarding to: the resolution of the mainbeam width, sidelobe level, sensitivity to the environment mismatch and the relation with low signal-to-noise ratio (SNR). Still at the same subsection it is presented the main disadvantages restricting the application of MFP by reducing its performance: the resolution of the ambiguity surface; and the inevitable inaccurate knowledge about the acoustic environment information from the high variability of the ocean both space and time which will introduce at the ambiguity surface multiple local maximums or false alarms.

Finally, the last section shows the model-based processing divided in three steps: the sample covariance matrix estimation, the Green's function (similar to the steering vector on the conventional beamforming the sonar array pattern) resulted from the simulations and the Matched field algorithm. Two matched field processors were then presented: the Bartlett matched field processor and the second one is the minimum variance distortion less processor (MVDR).

CHAPTER 3

Hausdorff distance as cost function for the inverse problem

Contents

3.1. Introduction	28
3.2. Definition	30
3.2.1 Maximum Hausdorff Distance	30
3.2.2 Mean Hausdorff Distance	32
3.2.3 Partial Hausdorff Distance	33
3.2.4 Median Hausdorff Distance	34
3.2.5 Combination of Hausdorff distance	34
3.3. Probabilistic formulation HD	35
3.4. Hausdorff distance temporal Translation	35
3.5. Rasterized of grid of simulation	36
3.6. Hierarchical Cell Decomposition	36
3.7. Gromov Hausdorff distance	37
3.8. Chapter Summary	38

3.1. Introduction

Object recognition algorithms are fundamental instrument in automatic matching sets of points. In our localization problem, we are interested on finding the minimal value of the distance transform, from a model-to-observation discrepancy map, measured by some cost-function, which indicates the possible location of the source. We will describe in this chapter the Hausdorff Distance metric and suggest to a future work the use of the Gromov Hausdorff Distance cost-function metric. Here will also be presented its benefits and differences used for underwater localization. The first one, called as Hausdorff distance, applied on only one metric space. It is evaluated using the Euclidian distance on extrinsic geometry, which is robust to topology changes (small deformations at the surface or small size variations of an object) but variant or even not robust to non-rigid deformations (change the shape of the same object considering different poses). The second called the Gromov Hausdorff distance, used for a non-rigid space applied on more than one metric space, evaluated using the geodesic

distance on intrinsic geometry, which are invariant to non-rigid deformations but not to topology changes, presented in this chapter to future works.

The Hausdorff Distance (HD) is a technique to measure the degree of resemblance among different sets of points that are superimposed to each other over a metric space. The HD technique outlined in this thesis is not new. Search in Web has revealed more than 42000 citations, among them 700 IEEE articles related with HD, been an important technique widely used in many areas such as: speech recognition [74], video recognition, computer vision [75], medicine [76] and [77], robotics [78], radar and satellite image processing [79], ship positioning [80], underwater vehicle classification [81] [82], sidescan sonar [83], and many other described in this article [84]. In the context of this thesis, it was first used in active sonar by Mours et al [85].

Dating back to 1905, in his PhD thesis: *On the continuity of complex variable functions* (French translation), Dimitrie Pompeiu defined the concept of distance between two closed sets, used in a domain of his thesis (complex analyses) [86], however the name nowadays referred as hausdorff distance, came few years later, in 1914, with Felix Hausdorff in his book *Basics of Set Theory* (German translation) [87]. Hausdorff considered all the basic properties Presented by Pompeiu, he generalized this metric in a slightly different way, considering in a metric space, point out the asymmetric distances from the partial forwards and backwards Hausdorff distance, and defining what is currently denoted by $H(A,B)$, commonly named bidirectional Hausdorff distance even after the Hausdorff's acknowledgment to Pompeiu in his three books editions: in 1914, pg. 430 [87], in 1927 - *Set Theory* (German translation), pg. 280 [88] and in 1957 translated into English version, pg. 343 [89] as well explained in [84] and [90].

Finally, the correct name of this metric should be referred to Pompeiu-Hausdorff distance, however after the acknowledgment to Pompeiu, in order to follow the literature and to avoid misunderstanding, we will adopt from now on as a Hausdorff distance technique.

The computation of the Hausdorff distance does not necessarily need to establish the one to one correspondence relationships between the elements of the two sets; therefore it may effectively process the situations where multiples elements in one set are associated (closest) with a single element of the other set. This is unlike most model-based processing techniques presents at the literature, which gives an explicit pairing (one to one correspondence). This feature is important because in case of missing point or fake detection (extra points) on any one of the two sets, all the sequences comparison would be associated with the wrong position on the other set if followed the one to one correspondence relationships on the HD.

The second important feature of this technique is the advantage that it takes into consideration the spatial proximity of each individual point in a rasterized grid of simulation. This feature makes it capable of considering the spatial properties in the measurement for comparison between two different set of points, meaning that it is more robust to the environmental mismatch comparing to those well-known localization techniques, such as for example the Matched Field Processing (MFP). The MFP is quite sensible to a shift in time on the Time Differences Of Arrival (TDOA - first arrival is used as reference), where even a small mismatch between the 2 sets of points, measured TDOA and modeled TDOA, may preclude its green's function from matching, which would clearly affect the accuracy of the location. The HD also offers an opportunity for a hierarchical cell decomposition strategy, defining a preliminary large cell grid for a rough first global search, and then refining the mesh size for a higher final accuracy, which is not possible using MFP and would result the same problem described above.

The basic difference between the HD and the MFP is that the MFP evaluates the position of the target based on the maximum value of the output correlator of the observed impulse response, which contains the information about the TDOA and Angles of Arrival (AOA) of all ray paths. The HD distance quantifies the similarity between the two measured and modeled sets, TDOA and/or AOA. The correct target location is then identified as the output from a global search for the minimal value, corresponding to a maximal match between those sets, theoretically being zero if both sets are identical. In presence of an environmental mismatch, an error would be introduced in the modeled sets, and induce a corresponding error in the estimated location of the target; however it seems that the impact of the modeling error on results from the HD cost function is far less critical than for the MFP correlation. The third advantage of using HD is the reduced computational runtime, comparing with the MFP and MMP. Fundamental reliability and robustness issue in presence of degradation are discussed later, as well as comparison with other techniques.

3.2. Definition

3.2.1 Maximum Hausdorff Distance

The Maximum Hausdorff Distance (MaxHD), described by Huttenlocher [91] in the field of image processing (most cited IEEE paper regarding to HD), is a technique to measure the degree of similarity (match) among all possible relative positions of two sets of points over a metric space. Here we invoke the HD for evaluating the distance between two 1D sequences of respectively modeled and measured TDOA, giving an interesting measure of their mutual suitable proximity.

Two bounded non-empty subsets A and B of an metric space are considered, one being the measured sequence of TDOA $\mathbf{R}_T = \{\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3, \dots, \mathbf{r}_x\}$, and the other one the modeled sequence of TDOA $\mathbf{S}_T = \{\mathbf{s}_1, \mathbf{s}_2, \mathbf{s}_3, \dots, \mathbf{s}_y\}$. The basic idea is, without loss generality, to define functions measuring the distance from each fixed element in one of the two sequences assigned to its nearest neighbor in the other translated sequence, and the distance between those selected points is defined by Euclidean norm $\|\cdot\|$. This way, a sequence of fixed point-to-point distances is obtained. Typically, the equation most commonly presented in the literature is the maximum bidirectional HD, defined as:

$$H(\mathbf{R}_T, \mathbf{S}_T) = \max\{h(\mathbf{R}_T, \mathbf{S}_T), h(\mathbf{S}_T, \mathbf{R}_T)\} \quad (1)$$

In this paper we will use the notations $\mathbf{h}(\mathbf{R}_T, \mathbf{S}_T)$ and $\mathbf{h}(\mathbf{S}_T, \mathbf{R}_T)$ for the direct, both forward and backward (reverse) HD respectively. The roles of the modeled and measured TDOA may be exchanged, resulting in two different sequences of distances. In general, those two “pseudo-distances” are not symmetrical $\mathbf{h}(\mathbf{R}_T, \mathbf{S}_T) \neq \mathbf{h}(\mathbf{S}_T, \mathbf{R}_T)$, depending on the number of points at each subset, and the combinations with the near neighbors themselves:

$$h(\mathbf{R}_T, \mathbf{S}_T) = \max_{r \in \mathbf{R}} [\min(\|r - s\|)] \quad i = \{1, 2, 3, \dots, x\} \quad (2)$$

$$h(\mathbf{S}_T, \mathbf{R}_T) = \max_{s \in \mathbf{S}} [\min(\|s - r\|)] \quad j = \{1, 2, 3, \dots, y\} \quad (3)$$

The final step for defining the HD consists of selecting the largest one among these minimal individual distances, which is the largest distance or the biggest mismatched point between the two sets of points.

In order to present the explanation of this technique, it will be applied on the data of the GIPSA-LAB experiment. The experimental setup will be described on the next chapter, here will only be presented the use of the HD for underwater localization.

Given two sets of data, one being the TDOA modeled (blue line - left) and the second being the TDOA measured (red line- left), presented at the Fig 1. The HD will then compare each index position on the first dataset with all elements from the second dataset (right). The final result called vector time difference between two sets will be composed of the minimal time interval for each index position (red square - right plot). This ensures that the closest position of each element will always be selected.

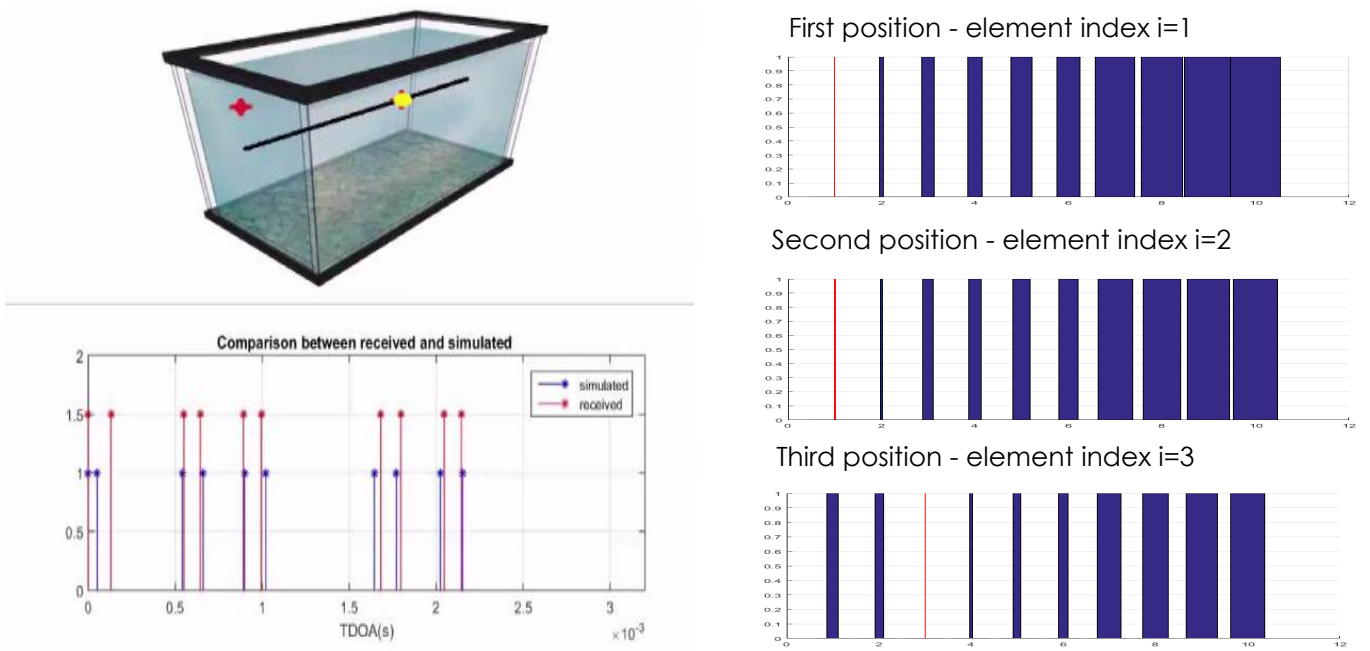


Fig. 7. Comparison between TDOA modeled and measured on the tank experiment (left), differences for each index of the first dataset with all the elements from the second dataset. This process is performed to all the index from the first dataset.

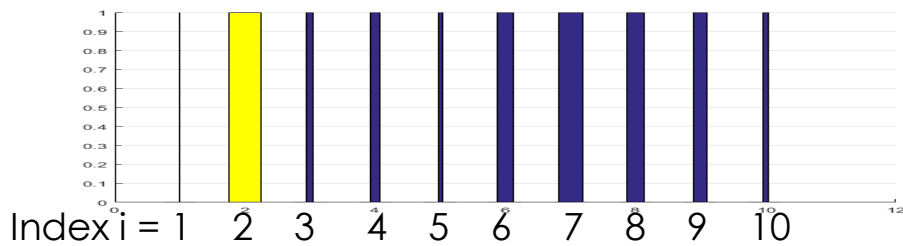


Fig. 8. Final vector of time differences between two datasets

The first variant of HD called Maximum HD will only select the value of the maximal on the minimal time difference vector. From the Fig. 7 and Fig. 8, the largest discrepancy between the two sets is located on the index position number two, represented for the yellow square. The others values of the time difference vector will be disregarded for this variant.

The MaxHD tolerates small variations in time at the set of TDOAs (most coming by environmental mismatch), and it is unaffected by variations in absolute phase or initial delay, being in that sense an incoherent process. The disadvantage of only selecting the farthest

distance appears in presence of outliers (a data observation or value that lies at an abnormal distance from the mean of other values in a data set); those extra-points un-legitimately dominate the final result of MaxHD, and may be responsible for huge mismatches. The next four variants of the basic MaxHD, presented in the following, mitigate this specific problem.

In the following, we will consider only one of the two sides MaxHD: the forwards or backward Hausdorff Distance; the choice will be based on the number of points in the set of modeled and measured. Then we will select the set with the less value to be used as reference, in order to avoid the missing point problem (due to occlusion), i.e. points that were not modeled or measured after over the time interval from the first path arrival. The decision of eliminate the second part of the bidirectional HD may solve the problem for missing points however it is also important to highlight that due to effects described on chapter 1, it is possible that at a particular distance and depth, the dataset either from the ray path propagation or from the measured TDOA, may contain only one or no path connect with the source (case of empty TDOA vector). In this specific case scenario, the output of the HD has high probability of a mismatch comparing to a correct position of the target, because the accuracy of this technique is direct related with the number of points used for comparison at each one of the two sets. One way to solve this problem is to try to simulate each one of variation in range and depths with the same number of vector elements, which in this experiment it was considered 10 elements, as shown at Fig. 7. This number came from a previous analysis in a realistic operational scenario, related with the average transmitted source power signal and the level of detection of the received array, provided by the SNR, allowing the detection of a source at a specified range, and may need to be increased to improve the accuracy of the technique in others scenarios.

3.2.2 Mean Hausdorff Distance

A first variant of the MaxHD, proposed by Dubuisson following the work of Huttenlocher, is the Mean Hausdorff Distance [92], where the average of the Euclidian distances is taken instead of its maximum. The MeanHD is defined as:

$$\bar{h}(R_T, S_T) = \frac{1}{X} \sum_{i=1}^X \left[\min_{r \in R} (\|r_i - s\|) \right] \quad i = \{1, 2, 3, \dots, x\} \quad (4)$$

$$\bar{h}(S_T, R_T) = \frac{1}{Y} \sum_{j=1}^Y \left[\min_{s \in S} (\|s_j - r\|) \right] \quad j = \{1, 2, 3, \dots, y\} \quad (4)$$

The main advantage of the MeanHD is that all points contribute to the final measure of similarity, which ensures that the others closest points will be take into account, and not only the ones that are the farthest one to each other, which can be outliers. In other words, the big mismatch that could arise from those outliers is divided by the number of elements of the referenced dataset and in this way the error can be reduced.

Fig. 9 shows the result of the mean direct forward Hausdorff Distance, considering the mean of all elements of the time difference vector.

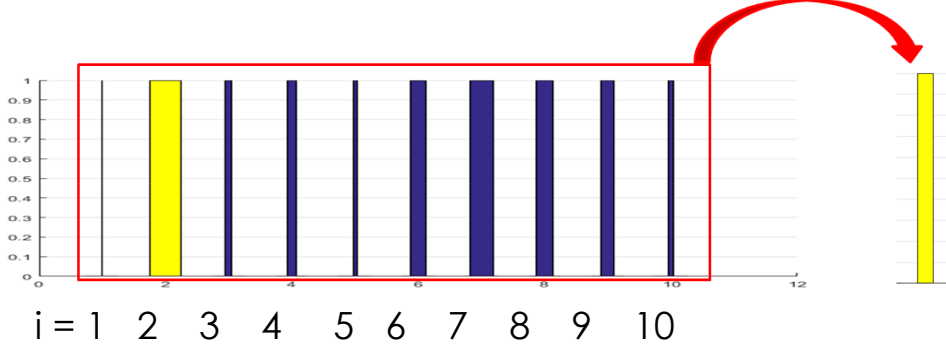


Fig. 9. The mean of all time difference vector is performed, given the result of te Mean HD.

3.2.3 Partial Hausdorff Distance

Some author's defined partial Hausdorff distance as a one side of the bidirectional HD, called here as a Direct HD, however in this work it will follow the notation of Huttenlocher [18]. The partial HD extends the definition of HD and it was developed to identify instances that are only partly visible in images (portions of two shapes). The definition adopted in this work is slight different form Huttenlocher, instead of taking the K_{th} ranked point of either subsets, we will adopted taking the average. The reason for this choice is that in some cases, most particular at long ranges, the set of TDOA measured may have different number of elements, due to the detection's limitation of the peaks imposed by noise. By taking the mean, we reduce the influence at the result coming from vector with different sizes.

$$h_K(R_T, S_T) = \frac{1}{K^{th}} \sum \left[\min_{r \in R} (\|r_i - s\|) \right] \quad i = \{1, 2, 3, \dots, x\} \quad (5)$$

$$h_K(S_T, R_T) = \frac{1}{K^{th}} \sum \left[\min_{s \in S} (\|s_j - r\|) \right] \quad j = \{1, 2, 3, \dots, y\} \quad (5)$$

The main advantage of this variant compared with the others two previous, is its stronger robustness to the outlier artifacts and also a missing point problem (because of the occlusion or failure of some feature detector), due to the elimination of the largest distances; however, in case of no extra-point detected, the Partial HD does not take benefit of the total amount of available elements, because the second part of the dataset in principle does not contribute to the final result. For the first experiment due to the limitation of 10 different paths, it was adopted values of K_{th} as 3 and 4. Values between 5 to 10, would give results close to either the MedHD or the MeanHD respectively. It is also possible varying the number of K_{th} , searching for the minimal output value. This process could be used to optimize this cost function, eliminating only the points that contain a high variation of error, however it is preferred to have when possible the same number of elements for all comparisons.

Fig. 10 shows the result of the partial direct forward Hausdorff Distance, considering only the mean of the 4Th first elements (red box) of the raked minimal distance vector.

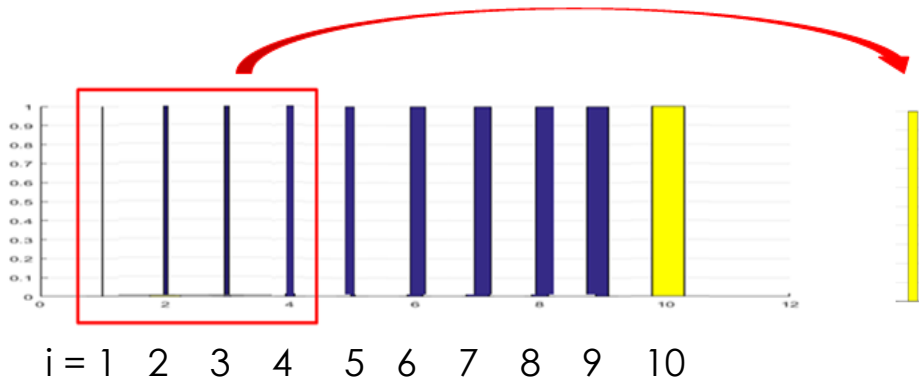


Fig. 10. The time difference vector is sorted by the minimal to maximal value and only the first 4 are used to find the average given the Partial HD.

3.2.4 Median Hausdorff Distance

The third variant, called the Median Hausdorff Distance (MedHD), it is a special case of the partial HD, proposed by Dubuisson [92], following the Huttenlocher's equations. Rather than taking the maximum or the average or only a portion of the Euclidean distances, The MedHD takes the value of the distance of the middle ranked vector of the chosen subset, or the mean of the 2 value of the middle ranked vector in a case of odd number vector. The reason is that different positions on the rasterized grid simulated may have also have close paths with the one recorded.

$$h^{50\%}(R_T, S_T) = K^{50\%} \left[\min_{r \in R} (\|r_i - s\|) \right] \quad i = \{1, 2, 3, \dots, x\} \quad (5)$$

$$h^{50\%}(S_T, R_T) = K^{50\%} \left[\min_{s \in S} (\|s_j - r\|) \right] \quad j = \{1, 2, 3, \dots, y\} \quad (5)$$

Fig. 11 shows the result of the median direct forward Hausdorff Distance, considering the mean of the two middle value of the ranked vector.

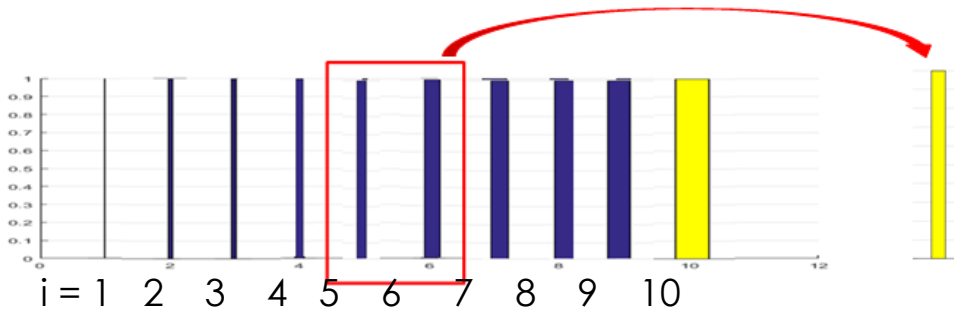


Fig. 11. The time difference vector is sorted by the minimal to maximal value and the value on the middle is used as a result of the Median HD.

3.2.5 Combination of Hausdorff distance

The idea to use combination of the previous HD variants, came from the knowledge of possible mismatch between the 2 sets of points, which can contribute to generate a secondary lobes (ambiguity position) in a wrong target position, introducing in that way a mismatch in our technique. Since that each different variant performs different elements combinations, it is

expect that secondary lobes occurs in different positions. As a result, the combinations can be used as a remedy to smooth this particular ambiguity problem, giving a more accurate localization in a presence of mismatches.

$$h_{\text{comb1}}(R_T, S_T) = h(R_T, S_T) + \bar{h}(R_T, S_T) + h^{50\%}(S_T, R_T)$$

$$h_{\text{comb2}}(R_T, S_T) = h(R_T, S_T) + \bar{h}(R_T, S_T) + h^{50\%}(S_T, R_T) + h_4(R_T, S_T)$$

3.3. Probabilistic formulation HD

The last variant was presented by Olson [93] in 1998, where he describes a probabilistic formulation HD of image matching in terms of maximum likelihood estimation. First, the normal Hausdorff Distance is performed, and then, instead of chosen a maximum distance, or a mean, or a portion of the vector distance, it will be fitted in a particular probability density function (fdp), normally uniform distribution with a mean “ μ ” and standard deviation “ ρ^2 ”. The fdp will have a high intensity peak considering the case of two resembling subsets, with the values of “ μ ” and “ ρ^2 ” close to zero, and a low intensity peak with a larger standard deviation otherwise, as shown at Fig. 12. The output of this variant will be the minimum at the inverse of the local maxima in the likelihood function. This variant will be more suitable to the case of non-cooperative case, due to the larger number of elements from the sidelobes.

$$h_{\text{fdp}}(R_T, S_T) = \frac{1}{\max_{r \in R} \left\{ p \left[\min(\|r_i - s\|) \right] \right\}} \quad i = \{1, 2, 3, \dots, x\}$$

$$h_{\text{fdp}}(S_T, R_T) = \frac{1}{\max_{s \in S} \left\{ p \left[\min(\|s_j - r\|) \right] \right\}} \quad j = \{1, 2, 3, \dots, y\}$$

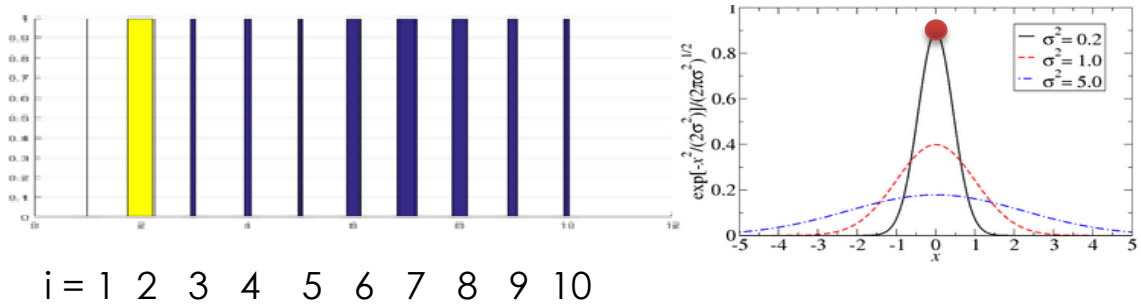


Fig. 12. Result of the fdp from the direct forward Hausdorff Distance. The red dot represents the interest peak value.

3.4. Hausdorff distance temporal Translation

One of the major problem of using HD for passive localization, considering the case of a cooperative source, is the critical choice of the reference points used for the comparison between datasets where if you correctly align these points, the rest of the set will possibly have a reasonably match. The first time of arrival, came from the matched filter, will be used at the reference in zero position in both sets and then compare the elements of each sequences. If some problem happens with the reference point due to occlusion or false alarm detection, this even small time variation will introduce a shift in time in all subsequent elements of the subset. One way to mitigate this problem is to use temporal translation. A vector with time

shift value, both positive and negative defined in an interval of time, will be added in one set of point on the Direct hausdorff distance equations 2 and 3. A global search will be performed looking for the minimal value of the output vector, resulting in a correction for this particular mismatch. It is clear that if the correct reference was adopted at the beginning, the value of the element of the time shift vector would be zero. The disadvantage of using the temporal translation for fixing the reference point position is the increases of the computation runtime as the time vector increases.

$$h(R_T, S_T, \tau) = \max_{i \in R} [\min_{j \in S} (|(r_i + \tau) - s_j|)] \quad i = \{1, 2, 3, \dots, x\} \quad \tau = \{\dots, -2\Delta\tau, -\Delta\tau, 0, \Delta\tau, 2\Delta\tau, \dots\} \quad (2)$$

$$h(S_T, R_T, \tau) = \max_{j \in S} [\min_{i \in R} (|(s_j + \tau) - r_i|)] \quad j = \{1, 2, 3, \dots, y\} \quad \tau = \{\dots, -2\Delta\tau, -\Delta\tau, 0, \Delta\tau, 2\Delta\tau, \dots\} \quad (3)$$

In a case of non-cooperative source, this problem is no longer relevant because the reference point will always be the higher intensity peak after the auto-correlation, however a new problem become evident, the secondary lobes (sidelobes) generated due to the cross correlation, which takes into a count not only the time of arrival but the influence of each other's times.

3.5. Rasterized of grid of simulation

The next step is to compute the Voronoi surface of each specify pixel location (x,y), obtaining the Voronoi surface array or two-dimensional distance transform. This surface array gives the distance for each modeled TDOA $\mathbf{s}_T$ at the location (x,y) to the measured TDOA $\mathbf{r}_T$ as shown at Fig. 13. The best matching (localization) is then performed through a global search for the minimal distance between those nonzero sequences, TDOA $\mathbf{r}_T$ into TDOA $\mathbf{s}_T$, or vice versa depending of the number of set's elements, since only one side of bidirectional HD was. If the modeled environment is close enough to the experimental environment, the simulations of acoustic propagation models should give, for the correct target location, the same sequence of TDOA, with an ideal HD equal to 0 (if and only if $\mathbf{R}_T \in \mathbf{S}_T$ and vice-versa), or practically reaching its minimum when every point of the modeled TDOA sequence is close to some elements of the measured TDOA sequence.

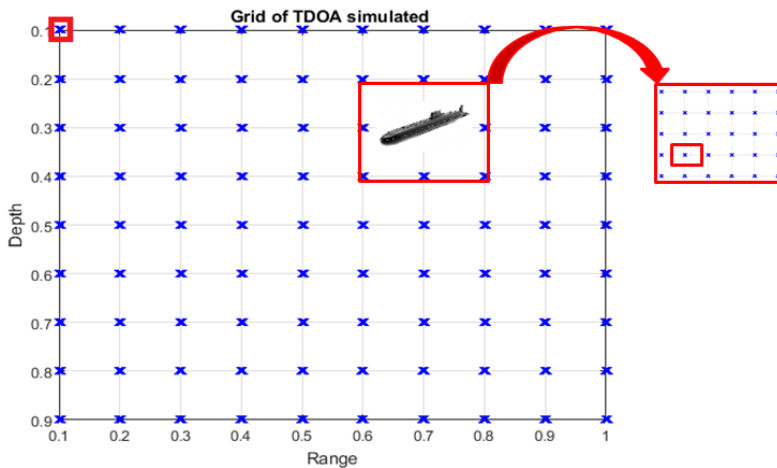


Fig. 13. Hierarchical cell decomposition on a rasterized of grid of simulation.

3.6. Hierarchical Cell Decomposition

The process of Hierarchical Cell Decomposition was also introduced by Huttenlocher [91], in order to optimize the computational runtime; this process is only possible due to the

Voronoi surface array. He notices that considering a small cell grid size, with a large number of points, would demand a high computation runtime, instead he realize that using a large cell grid size, with a few number of points, would reduce the computational processing time, however would also reduce the accuracy. To solve this problem, he adopted an efficient search strategy for locating model positions, using a multi-resolution hierarchical search that determines which cells may contain a position satisfying the criterion under a defined threshold, then subdividing the interesting cells currently best estimate, into sub cells (called next level or children of the tree cell decomposition), which are examined recursively until to the current cell size becomes small enough to the operation defined limit, as shown at the Fig. 13. The subdivision step takes all those cells that were labeled interesting and determines a set of smaller divisions (finer resolution). Those not selected cells are rejected. The final result is a list of transformations of the model that bring it into closer matching to the observations.

3.7. Gromov Hausdorff distance

This technique is proposed for future works. The concept of Gromov-Hausdorff distances extends the idea of the Hausdorff distance, measuring the similarity among different shapes, making precise the notions of closeness and convergence now considering more than one metric space. This distance is able to detect the metric similarity between the shapes as it operates on their metric structure, that is, different shapes are viewed as different metric spaces. Therefore allows us to compare how far two shapes are from being isometric, declared equal if and only if they are isometric $d(s_i - s_j) = d(r_i - r_j)$ [21]. The metric used for Gromov-Hausdorff distance is the geodesic metric mapped into a low-dimensional Euclidean space using multidimensional scaling (MDS), $d(s_i - s_j)$ and $d(r_i - r_j)$, which compares non-rigid shapes measuring the length of the shortest intrinsic path between a pair of points, leading to a bending-invariant shape comparison framework based on their pairwise distances from the two subsets. The geodesic metric is invariant to rigid transformations (reflections, translations, rotations).

Consciously, the origin of the name Gromov Hausdorff distance (GHD) have the same impasse regarding to who actually developed this technique. In 1975 D. Edwards published a paper titled: The Structure of Superspace [94], in which he marginally specifies the GHD in a different way but with equivalent terms. In few years later, back in 1981, Mikhail Gromov in his book, Metric structures for Riemann manifolds (French translation) [95], rediscovered this metric and generalized defining what is currently indicated at the literature nowadays, as explained in this article [96]. Search in Web has revealed more than 8000 citations, GHD, primary used in many areas such as: shape comparison [97], face Recognition [98], and others.

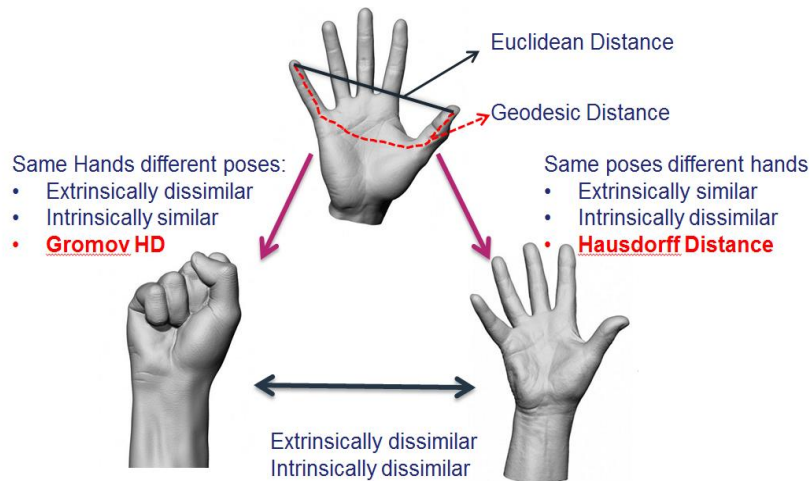


Fig. 14. Hierarchical cell decomposition on a rasterized grid of simulation.

Fig. 14 presents a simple example of the difference between this two metric. The HD is robust to compare different hands with the same pose (small topology changes), however cannot be used to compare different poses. The GHD is robust to non-rigid deformations (different poses – different position of the fingers at the figure), however it is not so robust when used to compare topology changes. Fig 9 also shows the difference of geodesic curvature of the object compared with the Euclidian Norm [99].

On underwater localization problem this new metric could be interesting because the reference point used to align two different sets is no longer needed. However a new problem emerges, the GHD is not sensible to work with 1D (TDOA) , as an example, considering 2 sets of points, $X = \{0, 1, 4, 10, 12, 17\} \subset \mathbb{R}$ and $Y = \{0, 1, 8, 11, 13, 17\} \subset \mathbb{R}$. Then we have two non-isometric metric spaces with the same distance set: $DX = DY = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 16, 17\}$. To solve this problem, the information from the Angle Of Arrival (AOA), coming from the beamforming techniques at the receiver must be included.

3.8. Chapter Summary

The first section of this chapter presents the historical background of Hausdorff Distance developed by Pompeiu. It was also presented some areas where it has been applied being most recognized in applications of image and video processing. Three main features seen as advantages of using HD were presented and were compared with MFP as well as some disadvantages of this technique. It was also presented one explanation of why the HD might be more robust against environmental mismatches compared with MFP.

The definition, equation and the HD variants was presented in the second subsection of this chapter. These variants might be used as a remedy to the outlier artifacts and also a missing point problem. The idea of combining different variants and the use of probabilistic formulation to reduce the problem of extra points was also presented.

The next subsection presented the influence of the critical choice to the reference points used for the comparison between sets, follow by the explanation of the applicability of HD in a 2D scenario (range and depths) in order to localize the true target's position, considering a rasterized grid of simulation. The process to optimize the computational runtime using Hierarchical Cell Decomposition was introduced next. Finally the use of the extended concept of HD, called as Gromov Hausdorff Distance was proposed for future works, and justified by some advantages of this new approach. The next chapter will present the results of the HD in a real experiment.

CHAPTER 4

GIPSA-Lab tank's experiment

Contents

4.1. Introduction	39
4.2. Measurement Setup	40
4.3. Simulation Results	46
4.4. Experimental results.....	48
4.5. Chapter Summary	51

4.1. Introduction

In order to test and prove the applicability of the Hausdorff Distance (HD) for underwater localization problems, in July 2016, an experiment was conducted in the tank of the GIPSA-Lab (Grenoble Institute of Technology, CNRS, University of Grenoble–Alpes, France). The experiment was highly simplified and performed in a controlled environment. The main purpose is to act as a proof of concept for the HD, given a better understanding of the technique and identifying potential advantages (more robust to environmental mismatches, less computational cost compared with previous techniques MFP, and insensitive to variation in phase) and limitations applied in a real experiment (sensitive to the first Eigen ray used as reference to the comparison between measured and modeled TDOAs). The measurement setup consists of two equal transducers, one as a receiver and another as a transmitter. The position of the transmitter is assumed to be known only for testing the accuracy of the Hausdorff distance cost function with a fixed: radial range, depth and bearing from the target to receiver. Due to the limitations of the tank and the experimental conditions, movement could not be added to the target (static experiment). As a result, the localization with Doppler Effect could not be analyzed. The localization was performed in two dimensions (2D), as range and depth. The angle of arrival (AOA) was not considered due to the limitation of the experiment considering a single receiver.

The localization procedure adopted was described on the first figure of this thesis. First, identify the time difference of arrival (TDOA) measured at the receiver, then simulate the TDOA, based on ray-path propagation, over a 2D grid with a defined step grid, then use the Hausdorff distance as a cost function to find the best match between the two set of data.

The performances of the proposed cooperative and non-cooperative localization techniques are demonstrated and confirmed by simulations with respect to the signal-to-noise ratio. The results in terms of the localization accuracy are presented as a conclusion.

4.2. Measurement Setup

The dimension of the tank is 1.5 meter length by 1 meter width by 1 meter height, with a 0.9-m water column depth. The geometry of the tank, geoacoustic parameters and position that comprise the model are illustrated in **Error! Reference source not found..** The radial source-to-receiver range was about 0.7 m, centered horizontally in the tank, which is less than the value of water depths. We set the position of the acoustic receiver at fixed 0.1 m deep and the transmitter was located at 0.3 m deep. The SSP was designed to be constant both spatially and temporally during the experiment (the SSP do not change with range being in this sense range-independent and because the small dimension of the tank it was also considered constant in depth). The Final SSP value was measured at 1474.3 m/s. Simulations considered a flat bottom configuration and the geoacoustic parameters of the glass bottom layer include the thickness of 2 cm and its estimated superficial sound speed, density and compressional attenuation are 4500 +-100 m/s, 2.70 g/cm³ and 0.40 dB/m/kHz respectively.

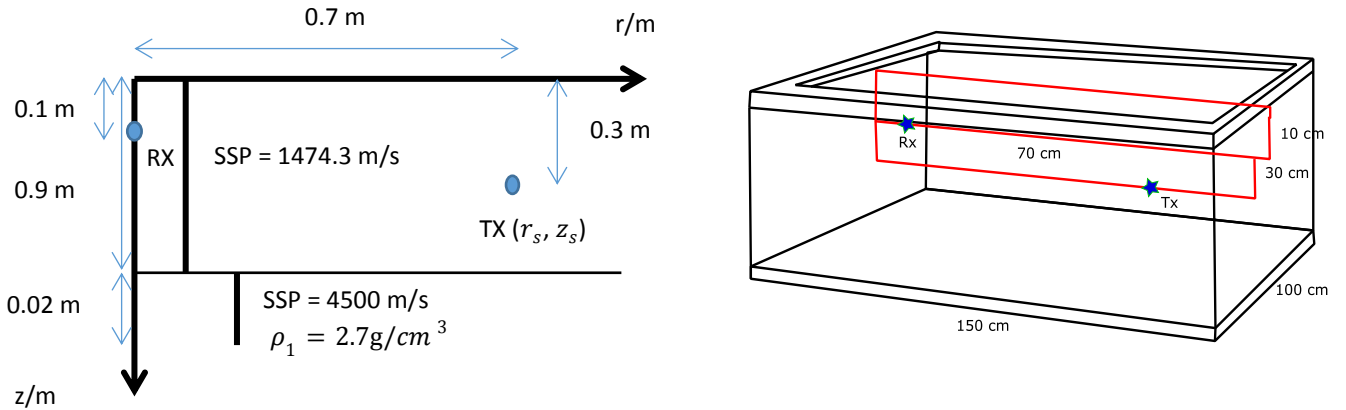


Fig. 15. Ray cross section

The transmitted signals featuring different narrow and wide-band codes, among which we considered only Linear Frequency Modulations (LFM) with time duration of 100 μ s. Both center frequency and bandwidth at 1MHz (500 KHz to 1.5 MHz frequency band). This signal was generated by the waveform generator 33500B, then amplified and transmitted to the underwater channel by the transducers ISL-0502. The sketch of transmission is shown at Fig. 16. The acoustic pressure propagate by the channel was then measured using an equal transducer, then pre-amplified and sampled by the data acquisition HS4 (A/D converter), with sample rate of 25 MHz and a resolution of 16 bits. The sketch of reception is shown at Fig. 16. The signal noise ratio SNR for the data was approximately 24 dB. Fig. 17 shows the laboratory facility used for the experiment.

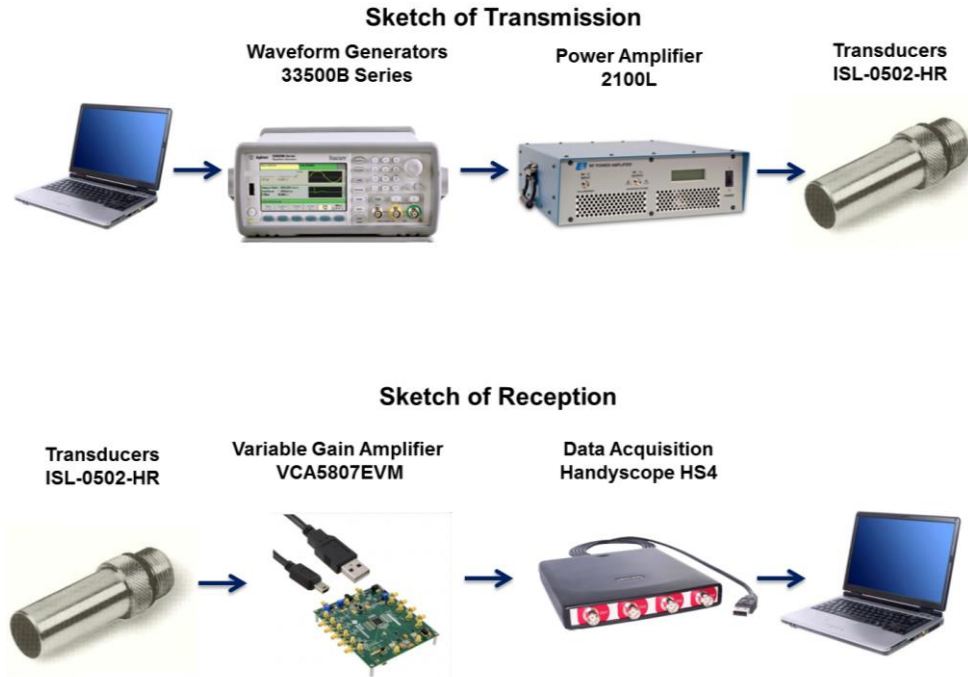


Fig. 16. Sketch of transmission and reception.

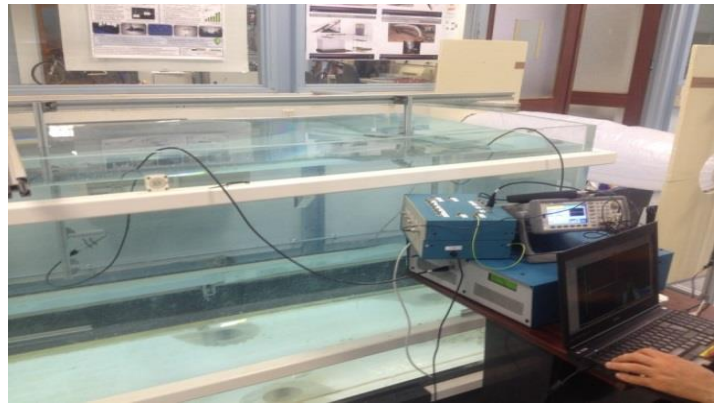


Fig. 17. Experimental facility.

The concept of beam spread is what defined the directivity of the sensors limited by 6 dB attenuation. The attenuation of the signal is more intense as the misalignment gets higher and follows the equation:

$$\phi = 2\sin^{-1}\left(\frac{0.5\lambda}{D}\right) = 6.6^\circ$$

Where:

λ = velocity (inch/ μ s) / frequency (MHz)

SSP = 1474m/s = 0.058in./ μ s

D = Element diameter (inch) = 0.5 inch

The transducers used both as transmitter and receiver, have approximately 7 degrees beam spread at the center frequency of the referred transmitted signal. Due to this directivity, the reflection of the tank's side can be disregarded, however, in order to record the entire set of different Eigen rays associated with each particularly take off angle for a specific location, the sensors must be mechanically rotate (tilt) and aligned to each other within a accuracy higher than 7 degrees. This process was performed for the 10 first Eigen ray and grouped based on the number of the bottom reflection. In this study, only three different groups of ray paths are considered, shown at Fig. 18. The first group defined as direct path with no bottom reflection (solid line red color), the second group considered as one bottom reflection (dashed line green color) and the last group with two bottom reflection (dash-dot line blue color). The groups composition are: first group 2 Eigen rays (direct path and one surface reflection (S)), second group 4 Eigen rays (one bottom reflection (B), one bottom and one surface reflection (BS), and so on, SB, SBS reflections), and third group 4 Eigen rays (BSB, BSBS, SBSB, SBSBS reflections).

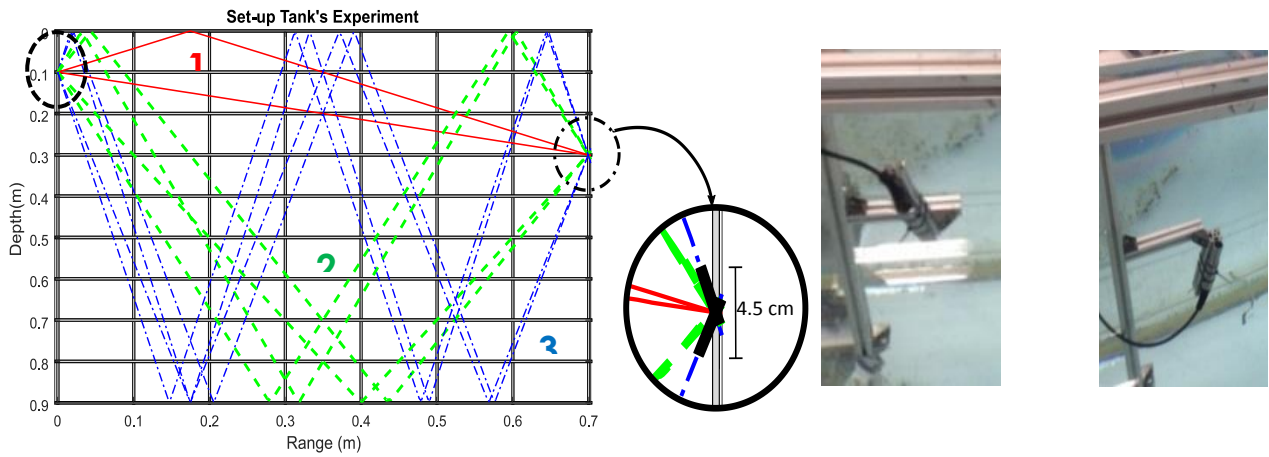


Fig. 18. The set-up of the ray paths from the ray propagation (left). Lower transducer tilt and Higher transducer tilt (right).

Due to this tilt mechanism, fixed at the middle of the transducers, the final position of each transducer shows a variation in depth location according to the transmitter and receiver, from the high angle of 85° , to the low angle of -80° , with a approximated 4.5 cm depth variation for each transducers, which represents 10% of the water column considering both combined; shown at Fig. 18. This introduces a significant variation into the TDOA and AOA due to the small dimensions of the tank, being the reason to we accept 10 % of error in depth position (9 cm). These small differences in time will be responsible to introduce an error or ambiguity either in target range or in depths. The measure procedure consists of align both transducers, recording each Eigen ray separately as shown at Fig. 19. Before each measurement in order to consider a flat surface reflection, an interval in time was applied to reduce the waves after each mechanic tilt. Superficial roughness height was limited around 2 cm. Fig. 19 shows only 9 different signals. The last one was disregarded due to the high value of noise. At the same figure it is possible to identify the 3 different groups in time of arrival, and it is also noted that for take-off angles bellow 7° spacing, it is possible to identify more

than one possible Eigen rays, reason for even after eliminating one recorded path, it was possible to detect 10 different Eigen rays. At the same figure it is also possible to identify 3 of 4 possible Eigen rays from the next group, however due to the low SNR and the presence of missing paths, the limit previous choose at two bottom reflections or the first 10 Eigen rays, is justify due to high attenuation caused by those reflections that conduct to the level of the signal below the level of noise.

The gain at the variable pre-amplifier (VGA), applied on a received signal was not kept constant during all the measurement and its value can be seen at the legend of the Fig. 19. The reason for this variation was that during the experiment, the primary task was to detect the TDOA coming from each Eigen ray. The VGA was used as a remedy against the problem of aligning the transducers due to the narrow angle spacing. Different from the MFP, the HD does not consider the amplitude of each Eigen ray, so this variation would not affect the final accuracy of the technique. This variation in a real environment could be seemed as interference either constructive or destructive at each moment.

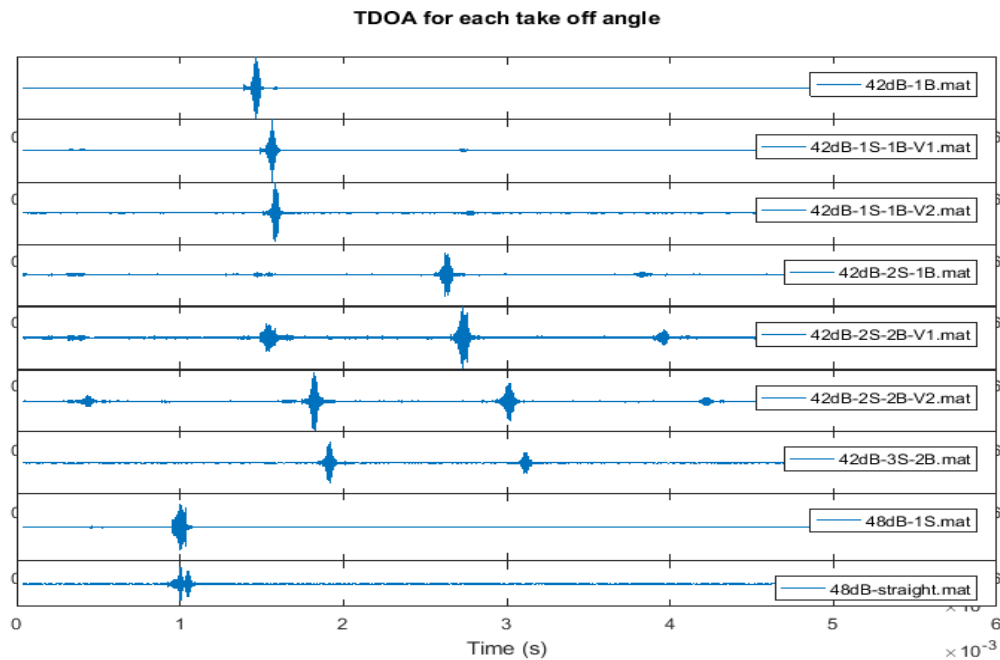


Fig. 19. TDOA recorded with 9 different take off angles.

Once that we measured all package containing 10 different Eigen ray, with different arrival time corresponding a different paths, called as complete received signal, these signals were summed in time using the transmitted signal as reference for synchronization of the different Eigen path. The impulse response of the channel was obtained considering two cases:

Cooperative case: This case is used when the transmitted signal is assumed a known waveform. The time difference of arrival (TDOA) is obtained by matched filter (correlation with the transmitted signal), and used as reference for the comparison with the modeled TDOA obtained from the ray path propagation, as show at Fig. 20.

Non-cooperative case: This case is used when the transmitted signal is assumed an unknown waveform or cannot be estimated, considered as a fully passive configuration. The time difference of arrival (TDOA) is obtained by the auto-correlation of the received signal. This process generates secondary lobes which contribute to a reduction of accuracy. It is most used in a platform like a submarine where rather than transmitter a signal (sonar array), which would give its position, it listen what is happen while keeping the most undetectable possible.

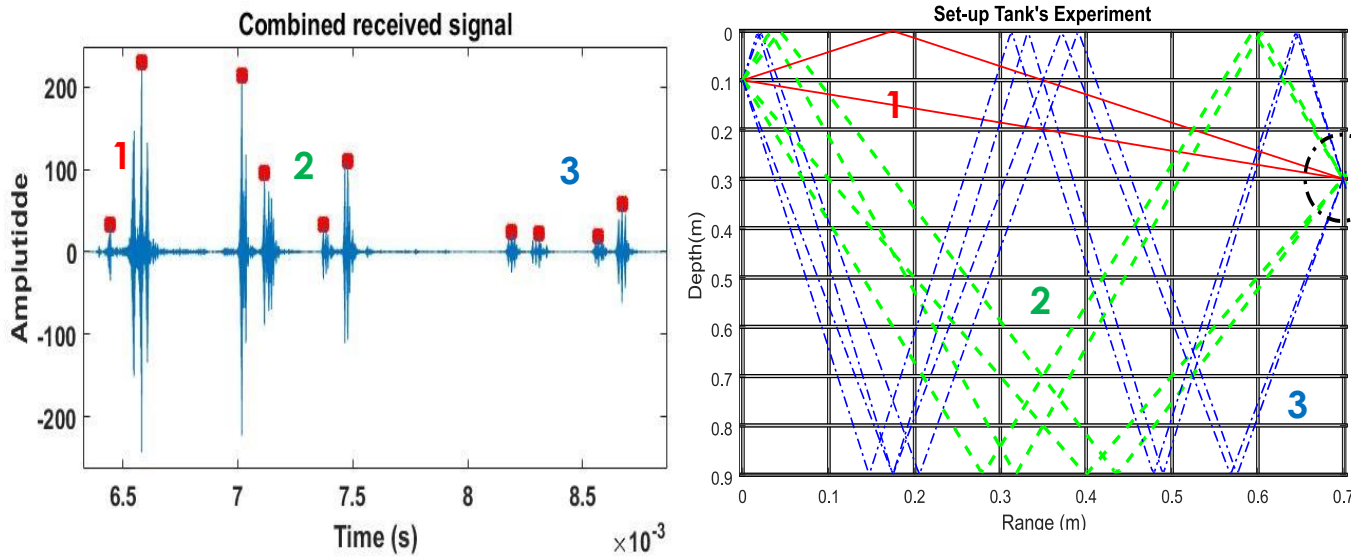


Fig. 20. Cooperative case – impulse response obtained by matched filter – time domain (left), associated with the correspondent Eigen ray (right).

Fig. 21 shows the difference of cooperative and non-cooperative cases. The TDOA was reduced to 4 (right plot - red lines) to simplify the problem because the final number of TDOA after the autocorrelation follow an arithmetic progression described on equation.

$$NF = \frac{N(N+1)}{2} + 1 = 7 \quad N = \text{Number of TDOA} - 1$$

The secondary lobes are created by the interaction of each one of the TDOA with each other, so in a case of mismatch in one of the Eigen ray, this error will be propagated to the others, reducing the accuracy of the target. In Fig. 21 (right plot), the secondary lobes are represented by the blue line.

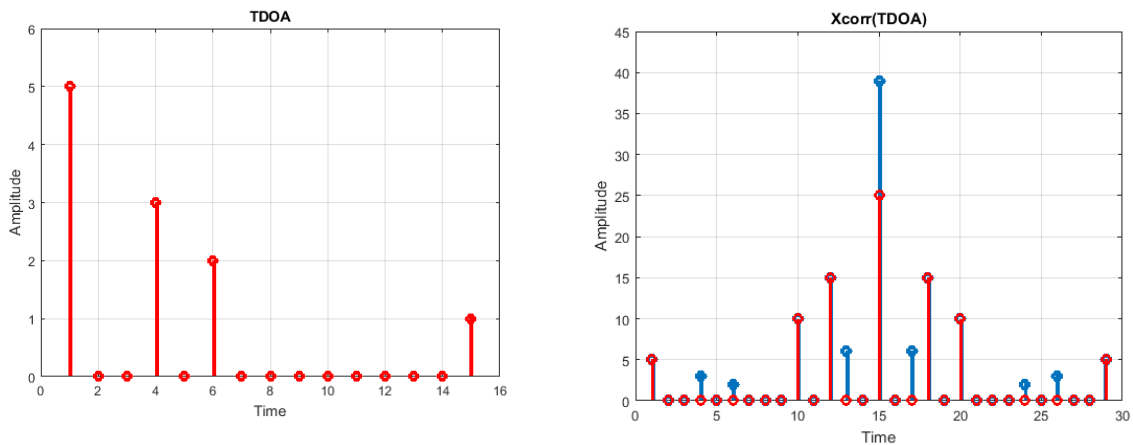


Fig. 21. Difference of Cooperative case (right) and Non-cooperative case (left) with secondary lobes (blue lines).

The ray path propagation theory was described in chapter 1. As presented below, the received signal is composed of several arrivals that are the time shifted and attenuated versions of the transmitted signal. The time duration of the transmitted signal was choose to avoid overlaps and interference between signals from different paths. The time information provides sufficient information to determine the source location, considering the well-defined environmental conditions.

Fig. 22 shows: a) the Sketch of the tank experiment, where the red dot is the position of: transmitter (top) and receiver (follow the black line), and the yellow dot is the position of the TDOA simulated, b) shows the comparison of the TDOA simulated (blue color) and received (red color) and c) shows the TDOA simulated considering a fixed depth and varying the range from 0.1 m to 1 m with a step grid of 0.1m, the red square is the selected TDOA simulated used to compare with the measured in b). The left image shows the TDOA simulated in the correct target location (yellow dot is situated at the same location of the red dot). It can be noted from the comparison that this position presents the most resemblance between simulated and measured. The right image shows the comparison considering a wrong position of the target. It can be noted that there is a difference between the two sets of TDOA. The HD measures these differences and show as output the position of most resemblance between the two sets as the estimated target position.

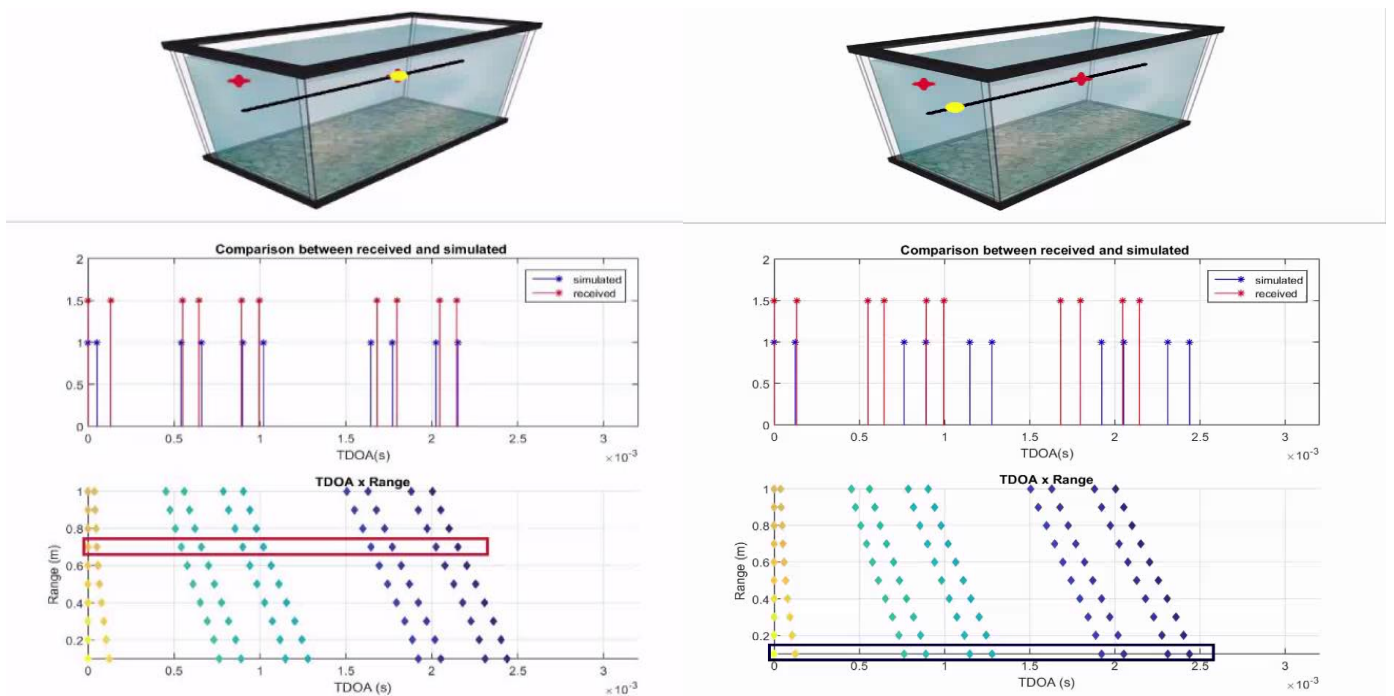


Fig. 22. Sketch of the tank (top), Comparison between TDOA modeled and measured (middle) and TDOA modeled for a fixed depth with variation in range from 0 to 1m, with step grid of 0.1m.

4.3. Simulation Results

The simulation was divided into three different scenarios. These scenarios are tested using the same configuration for two different systems, as cooperative and non-cooperative, to directly compare the results from each system.

Scenario 1 - All the ray paths have the correct TDOA. We do not consider any time variation at the received TDOA: Here we consider that the environment is well defined, without any mismatch of the bottom depths and SSP variations. This situation corresponds to the best possible scenario; however, it appears to be improbable considering the variability of real sea environment, including variations of the SSP, imprecision on the bottom depths, and mismatches in transducers locations.

Scenario 2 - Small random time variations are added in all different Eigen ray at the received TDOA, representing possible mismatch. This variation was limited at $60 \mu\text{s}$, either to positive or negative to the true simulated value. The limit of $60 \mu\text{s}$ was chosen based on the value of the SSP considered at 1474.3 m/s , which in this experiment represents a mismatch maximum at around 0.09 m (10% of the water column). This scenario corresponds to the worst possible case, representing some unpredictable variations in the environmental parameters, which are most commonly in the bottom depths and/or the SSP.

Scenario 3 – Different from the scenario 2, where a random time variations were added in all Eigen rays, in this configuration, we assumed that some random amount of Eigen rays are correct measured, meaning that no error was introduced at the TDOA, and for the remaining Eigen rays the value modeled was increased by a random time variation limited at $60 \mu\text{s}$. This scenario was the closest to the experiment, where some ray paths were measured with no time variations and some presented small time variations introduced by the different depth value due to the mechanic tilt. On Fig. 22 was illustrated this variation of TDOA modeled and measured to some Eigen rays. Some Eigen rays presents no time variation while others a small shift in time at the correct position.

In both systems, the transmitted signal was a linear frequency modulation (chirp) with time duration of $100 \mu\text{s}$ and a frequency range of 500 KHz to 1.5 MHz , same configuration for the tank experiment. The geoacoustic parameters such as bottom configuration and the value for the SSP was constant equal to 1474.3 m/s , same as recorded at the experiment. The source power was varied, with nine equally spaced values; from 150 dB to 90 dB for $1 \mu\text{Pa}$ at 1 m . 250 realizations were performed for each one of nine source power value.

For the first simulation, we consider a cooperative system, where the transmitted signal is considered as a known waveform with time duration less than the next time arrival ray path, to avoid interference between different Eigen rays for the correlation techniques. In the three different scenarios, four different localization techniques were evaluated, and the results are presented in Fig. 23: (i) Maximum Hausdorff distance (selects the biggest difference of TDOAs); (ii) Mean Hausdorff distance (mean of all of the difference between TDOAs); (iii) Correlation of the simulated signal with the received signal, which takes into account the

phase of the signal; and (iv) Correlation considers the signals envelope, while the phase is disregarded. It was adopted a 0.01m step for the grid of simulation both in range and depths.

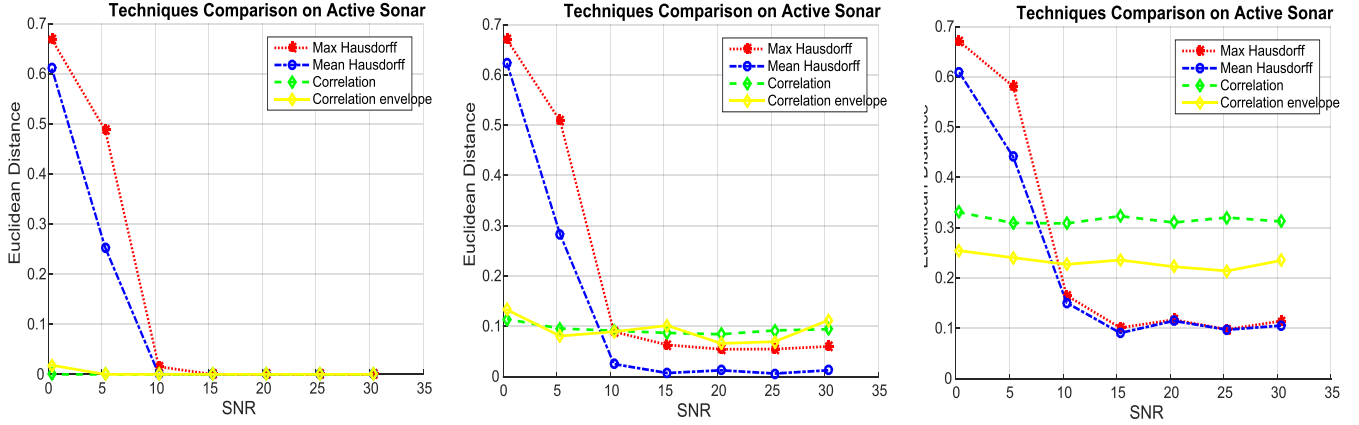


Fig. 23. Cooperative case: First scenario – well-known environment, no variation in time. b) Second scenario – A random time variations are added in all Eigen Ray. c) Third scenario – A random time variations are added in some random amount of Eigen ray.

Fig. 23 shows the result for each scenario, given the Euclidean distance (depth and range) for each SNR. For low SNR (less than 10 dB), the correlation techniques provide better result compared with HD and the reason is the defined high value of threshold (9 dB) after the matched filtering to detect the peaks (TDOA). At low SNR the HD fails because it does not correct detect all 10 Eigen rays, as a result a new detector peak technique was studied after this experiment. For high SNR however (more than 10 dB), the HD presented a better result. The Mean Hausdorff Distance for the Third scenario presented the best result and the reason was that in this particularly scenario, only a random partial number of Eigen rays were increased by a small time variation, those remaining Eigen rays, without added time variations contributed to soften the final result given a best accuracy to the localization. All simulations suggest that the HD is more robust against possible mismatches between the TDOA measured and modelled.

For the second experiment, we consider a non-cooperative system. As a consequence, the transmitted signal is unknown. For this case, the localization was performed with only two techniques: the Hausdorff distance and the mean Hausdorff distance.

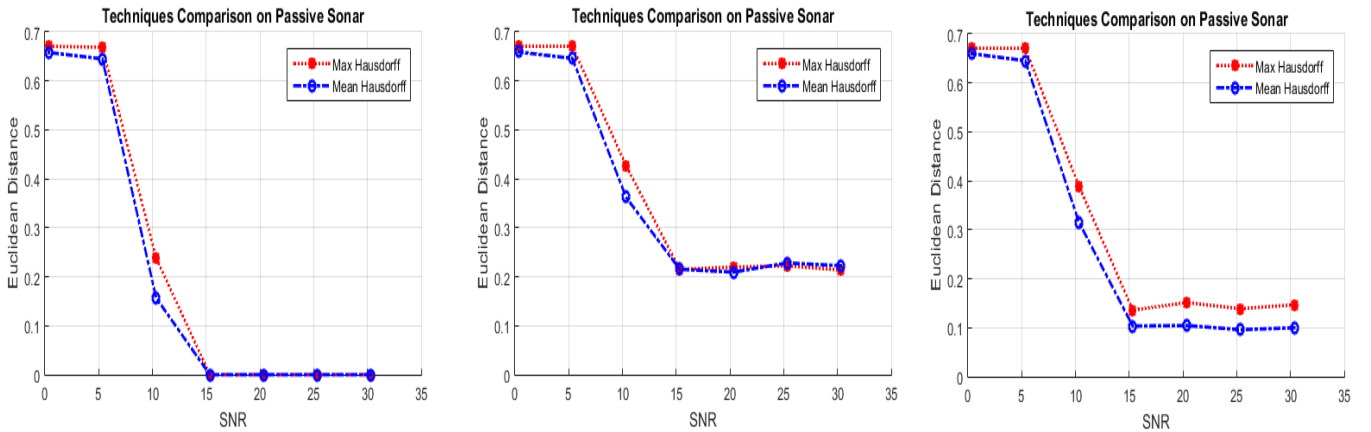


Fig. 24. Non-Cooperative case: First scenario – well-known environment, no variation in time. b) Second scenario – A random time variations are added in all Eigen Ray. c) Third scenario – A random time variations are added in some random amount of Eigen ray.

Fig. 24 shows the result for each scenario. It can be observed that in a non-cooperative system the results are worse than the cooperative system, and the reason is the introduction of the secondary lobes coming from the output of the cross correlator. The small variation in time from some of the Eigen rays is then propagated to the secondary lobes and contributes to reduce the final accuracy of the target location. This loss of sensibility was expected in this case and it is the reason for instead of applying the cross correlation of the received signal, try to estimate the transmitted signal and perform the matched filtering in order to reduce this error. Now, the new break point of the SNR is 15 dB compared with 10 dB for the cooperative system. Overall the final value of error for this case is near the double of the cooperative system. Once more, the simulations suggest that the Mean Hausdorff Distance is more robust against possible mismatches between the TDOA measured and modelled.

The second benefic of using HD is the reducing computational run time. As a comparison, the processing time for only one realization, Hausdorff distance takes 0.02 s, the correlation in frequency domain takes 1.15 s, and the correlation of the signal envelope in the time domain takes 2.48 s.

4.4. Experimental results

The results of the experiment will be divided in two cases, following the same as presented for the simulations: the first case describes a cooperative system and the second describes a non-cooperative system. The experimental results will be compared with the one obtained from the simulations for the associated SNR of the experiment, which was approximately 24 dB. All the follow analysis will consider the use of two Hausdorff distance variants: the first being the Maximum Hausdorff Distance and the second being the Mean Hausdorff distance.

To compare the two variants, the results are normalized and kept to the same logarithmic scale (same reference color mapping), allowing direct comparison of the accuracy of each variant on each followed image. The real target is located by a red star at the intersection of the red dashed lines. The minimum value of the matrix is represented by the yellow cross marker (+).

The first case in analysis describes a cooperative system. Fig. 25 shows the results of both variants considering the step grid used for the ambiguity surface as 0.1m, both in range and in depth.

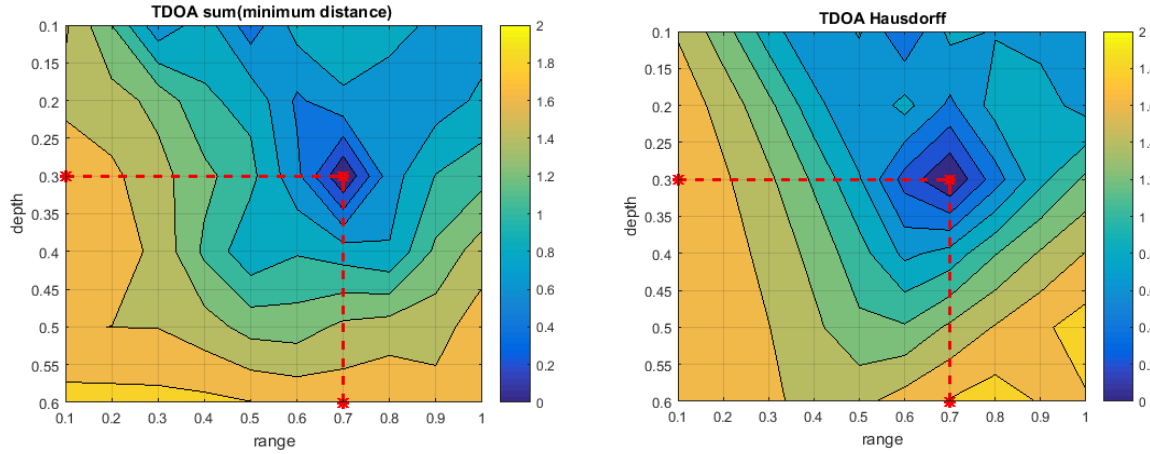


Fig. 25. Maximum Hausdorff distance (right) and Mean Hausdorff distance (left) applied in cooperative systems with step grid of 0.1m. Red star is a real position of the target. Yellow cross marker is the minimum value of the matrix error.

Due to the low spatial resolution of the previous image (high value of the step grid), both variants give the correct location of the target. The dark blue means the position of the minimum error that correspond the best result. The Mean Hausdorff Distance presented a small dark blue area meaning that the variance of error is less than the Maximum Hausdorff distance. In order to increase the perception of accuracy, the same technique was applied for a step grid of 0.01m (10 times smaller), obtained by the interpolation of the TDOA modeled, shown at Fig. 26.

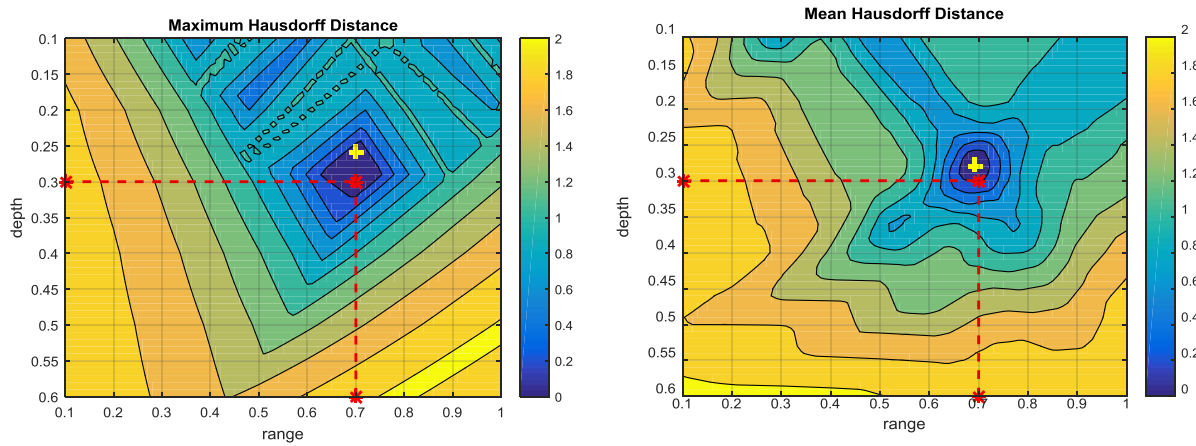


Fig. 26. Maximum Hausdorff distance (right) and Mean Hausdorff distance (left) applied in cooperative systems with step grid of 0.01m. Red star is a real position of the target. Yellow cross marker is the minimum value of the matrix error.

The results with a higher spatial resolution shows that the estimated position from Mean Hausdorff distance represented by the yellow cross is closer to the true target position compared with the Maximum hausdorff Distance. This result was the compatible with the one obtained by the simulations.

Tables 1 show the results after the interpolation with the Euclidian distance calculated in comparison with the real position, at 0.7 m in range and 0.3 m in depth.

Table 1. The position error for different Hausdorff distance.

Factor	Aspect	Maximum Hausdorff	Mean Hausdorff
Estimated	Range (m)	0.7000	0.6900
	Depth (m)	0.2600	0.2800
Error	Range (m)	0.0000	0.0100
	Depth (m)	0.0400	0.0200
Experimental error (m)		0.0400	0.0224
Simulation error (m)		0.055	0.015

The final value of error from the experiment is then compared with the one obtained from the simulations considering the Third scenario. The results are quite similar with the Mean HD the best variant for this experiment.

The second case describes a non-cooperative system, shown at Fig. 27. The final accuracy for this case is worst compared with the cooperative systems. These results are consistent with the simulations. In non-cooperative systems, any small variation in time, and or amplitude, presents a worst effect to the accuracy of the localization due to the propagation of error from the cross correlation, generating the secondary lobes. In our experiment, this bias was generated by two principal factors: the first one is provoked by the mechanical tilt of the sensors, as indicated in the earlier description here. This introduces a small time variation in the arrival time. The second factor, each path was recorded with a different amplifier gain, in order to optimize the quantization interval, which may increases the intensity of wrong position of the secondary lobes after the cross-correlation.

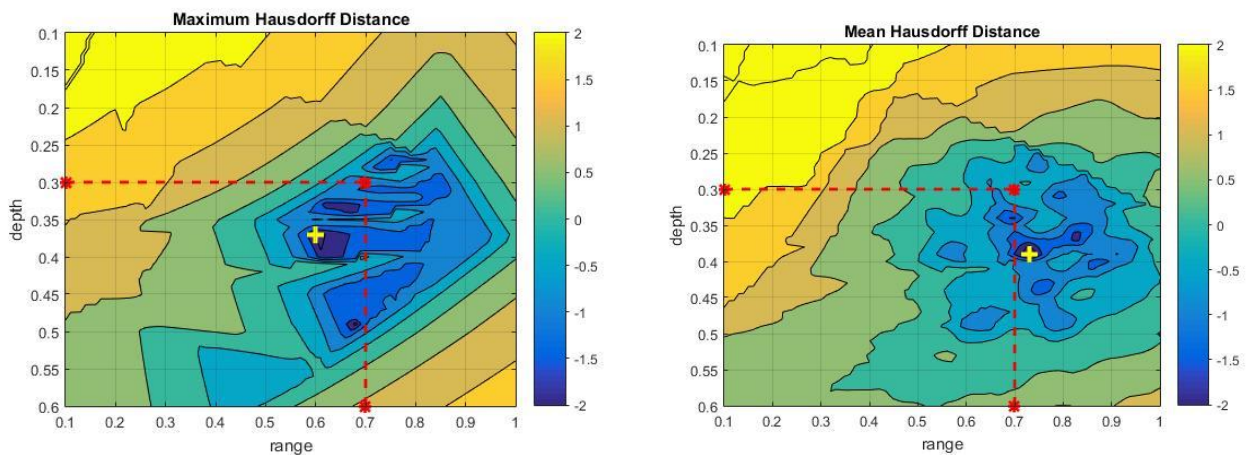


Fig. 27. Maximum Hausdorff distance (right) and Mean Hausdorff distance (left) applied in non-cooperative systems. Red star is a real position of the target. Yellow cross marker is the minimum value of the matrix error.

In this configuration, shown at Fig. 27, the real target position (red star at the intersected dashed lines) is not inside of the dark blue area. The minimum value (yellow marker), is closer to the real target using the Mean Hausdorff distance. This result resembles to the one

obtained by the simulation. The second important conclusion noted by the images is the appearance of ambiguity points represented by the different dark blue area locations. As the value of small variation in time increases on the TDOAs, the contribution of these ambiguity points at the output of the HD become most important, which may result in an impossibility of localize the target close to the true position.

Tables 2 show the results after the interpolation with the Euclidian distance calculated in comparison with the real position, at 0.7 m in range and 0.3 m in depth.

Table 2. The position error passive system.

Factor	Aspect	Maximum	Mean
		Hausdorff	Hausdorff
Estimated	Range (m)	0,600	0,730
	Depth (m)	0,370	0,390
Error	Range (m)	0,100	0,030
	Depth (m)	0,070	0,090
Experimental error (m)		0.122	0.095
Simulation error (m)		0.14	0.10

The final value of error from the experiment is once more compared with the one obtained from the simulations considering the Third scenario. The Maximum Hausdorff distance presents a higher value of error. The results also suggest that the Mean Hausdorff distance is more accurate in range ($\sim 0.03\text{m}$ of error) than in depths ($\sim 0.09\text{m}$). The results obtained by a cooperative case are around three times more accurate than the one by non-cooperative case. This conclusion was important for further studies regarding to estimating the transmitted signal rather than apply the cross correlation in order to avoid or reduce the effects of secondary lobes.

4.5. Chapter Summary

The purpose of the GIPSA-LAB experiment was to gather data under experimental conditions, used to validate the proposed inversion technique with respect of the precision using a real target. The detection of the arrivals angles (AOA) was not possible due to the limitation of the experiment, considering a single receiver. The target was motionless; as a consequence it was not possible to analyze the Doppler.

An innovative and efficient Hausdorff distance technique, responsible for a comparison of the measured and modeled time difference of arrival (TDOA), was used in a cooperative and non-cooperative underwater localization. The first one considers a known transmitted signal. The received signal is matched filtered (correlated with the transmitted waveform). The

second, fully passive configuration, considers an unknown transmitted signal. The received signal was cross-correlated which generated secondary lobes, responsible for reducing the accuracy of the localization in presence of mismatches due to the propagation of error. During the experiment, a mechanical tilt needed to be used due to the narrow beam spread of the transducers. This tilt introduced a variation at the depths of the sensors considered maximum of 10% of the water depth, approximated as 0.09 m. this variation was important to evaluate the proposed technique in presence of mismatches.

The experimental setup made in a tank has proved that it is possible to localize real signals in a two-dimensional scenario, range and depths, with satisfactory precision even with only one sensor at the receiver, and without the need for prior information about the source. These experimental results provide an important database for further research. These two variants of Hausdorff distance used a-priori for image localization have been applied at simulations and experimental data and the results have suggested that the HD is more robust against possible mismatches between the TDOA measured and modelled applied on underwater localization. The mean Hausdorff distance provides better results when applied to underwater localization because it can smooth some large discrepancies of the differences between the TDOA measured and modeled. These two variants have also presented an improvement at the computational time, compared with the correlation techniques. This is a potential opportunity to enable real time systems location, as in range and depths, using on an arbitrary source.

New techniques to estimate the signal, and also to detect peaks for low SNR, need to be studied in order to improve the precision of this passive system localization, in order to avoid ambiguity location points that can be caused by secondary lobes.

CHAPTER 5

Alma 2015 Experiment – Spatial Diversity

Contents

5.1. Introduction	53
5.2. The ALMA 2015 experiment	54
5.3. Spatial diversity versus beamforming	58
5.4. Results with only one hydrophone	61
5.5. Results with Array - Spatial diversity.....	67
5.5.1 SSP close to the source	70
5.5.2 SSP close to the receiver.....	73
5.6. Best Configuration.....	78
5.7. Minimal number of Hydrophones.....	79
5.8. Chapter Summary	81

5.1. Introduction

The main purpose of this chapter is to present the at-sea experimental results of the technique Hausdorff Distance (HD) used to validate the underwater inversion in a real environment. The results of this experiment will be presented in two chapters. This chapter describes the experiment and presents the results based on the spatial diversity. The chapter number 6 presents the results of beamforming technique and ends up with the comparison of both techniques. The data set analyzed here was collected during the DGA campaign ALMA 2015, which took place in a shallow water environment of the southern coast of France (up to 100m deep on the Mediterranean Sea). The ALMA 2015 sea trial was intended to study of the influence of fluctuations due to wavefront distortion and decoherence effect on the medium, using different temporal and spatial scales, which makes the underwater localization a challenge to achieve. Acoustic data were measured over a 10m vertical linear array (VLA), composed of 64 hydrophones. The position of the transmitter is assumed to be known only for testing the accuracy of the Hausdorff distance cost function with a fixed distance, depth and bearing from the target to receiver. The 2-D localization, in range and depth, is performed by matching the patterns of time difference of arrival (TDOA) and differently from the previous experiment, the information of the direction of arrival (DOA) was also considered, between

respectively measured and modeled sequences. The DOA was obtained explicitly by the beamforming and implicitly by the spatial diversity due to the time delay of each hydrophone. Several variants of the Hausdorff Distance were applied, firstly separately in each single hydrophone, and then combined in order to improve the localization accuracy, reducing the ambiguity both in depth and in range. The performance is evaluated in terms of the localization accuracy of the proposed method, in a context of **passive localization with a cooperative system** considering a motionless target (Static Target).

5.2. The ALMA 2015 experiment

In October 2015, during three days of ALMA 2015 campaign (Acoustic Laboratory for Marine Applications) [74], designed and managed by DGA Naval Systems, experimental acoustic and environmental data were collected in a shallow water environment off the southern coast of France, near the harbor of Toulon. Fig. 28, presents the location of the single acoustic projector at the coordinates ($43^{\circ} 04,477\text{N}$, $05^{\circ} 41,946\text{E}$), and also the receiving 10m-high array (64 vertical linear passive array hydrophones (VLA), distributed in depth from 52.5m to 62.3m, equally spaced with 15cm of separation between hydrophones, at the coordinates ($43^{\circ} 07,136\text{N}$, $05^{\circ} 36,295\text{E}$)). The wind's direction and speed was used to evaluate the sea state condition during the experiment, being an average at 9 knots and its direction is represented by the black arrow at Fig. 28.

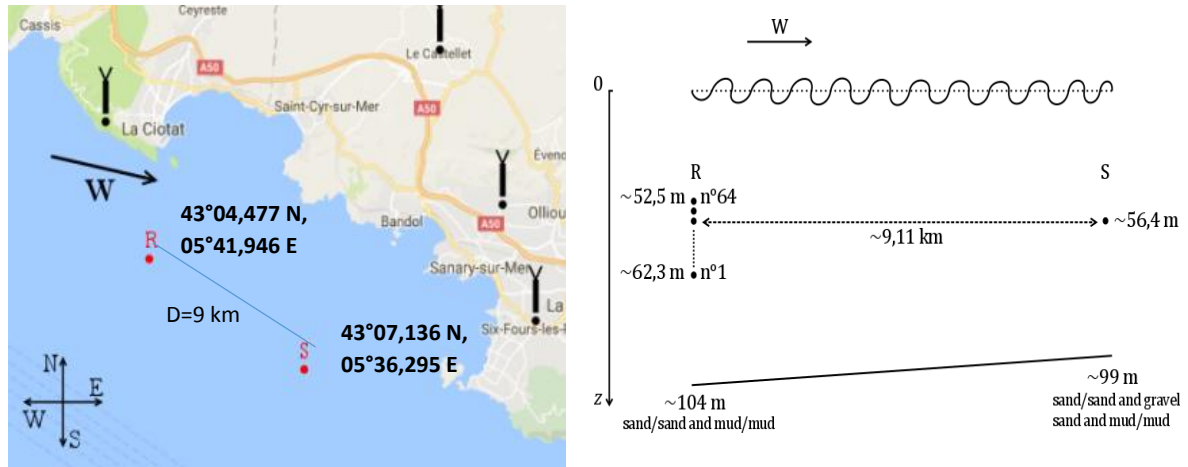


Fig. 28. Top view of the experimental setup measurements region (left), Skech of the experiment (right).

The seafloor was roughly flat, with an average depth about 100 m, varying from $99 \pm 3\text{ m}$ close to the source location and $104 \pm 6\text{ m}$ close to the receiver position, with a sediment cover constantly sandy or gravelly-sandy. Subsequent simulations assume that the geoacoustic parameters of the bottom layer **include the thickness of 2 m and its estimated superficial sound speed, density and compressional attenuation are $1780 \pm 100\text{ m/s}$, 1.8 g/cm^3 and 0.10 dB/m/kHz respectively**. The radial source-to-receiver range was about 9.1 km, which represents around 90 times the value of water depths, as shown at Fig. 28.

Six SSP measurements were performed during the 3 days experiment, the first three being close to the source and the remaining close to the receiver location. The black line measured on the first day; blue line, second day and red line last day of the experiment shown at Fig. 29.

The SSP is more stable close to the surface than close to the bottom. The SSP measured at the receiver location presented at the last day of measurements the highest fluctuation (12 m/s at 85 m depths).

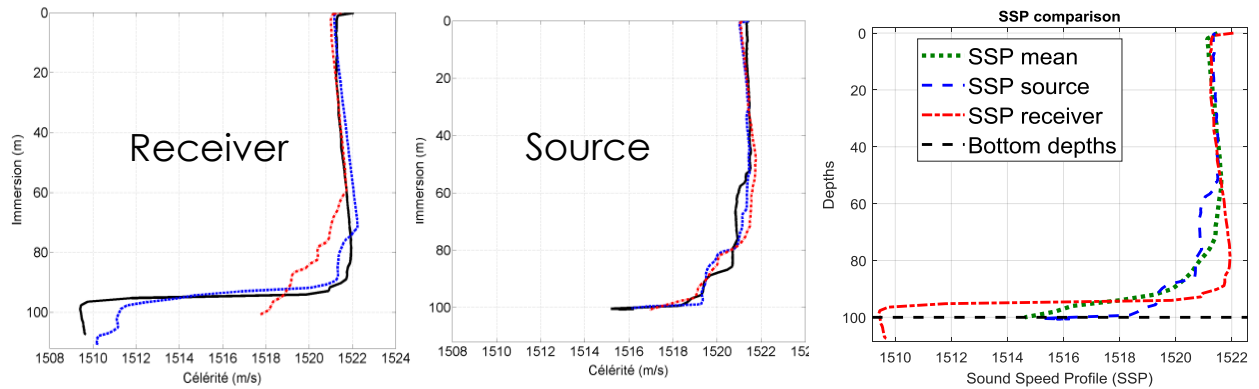


Fig. 29. SSP of the experiment. SSP measured close to the receiver for each day of the experiment (left), measured close to the source (middle). In both plots the black color represents the first day. On the right it is presented the SSP used for the modeling.

During the simulations, three SSP were analyzed Fig. 29 (right). The SSP close to the source of the first day was simulated using 2 different ray path propagation programs from THALES. Fig. 30 shows the comparison of the TDOA simulated with the three different SSP. The first one was measured close to the receiver, the second one measured close to the source, both cases considered the measurements on the first day, and the last one was performed by the mean in depth between both SSP measured. From the Fig. 30, it is possible to notice a resemblance of the three different SSP for the early arrivals (0 to 0.05s). The SSP close to the source and the SSP mean presents a high value of resemblance to a majority of the arrivals. The late arrivals however, presents some dissimilarity.

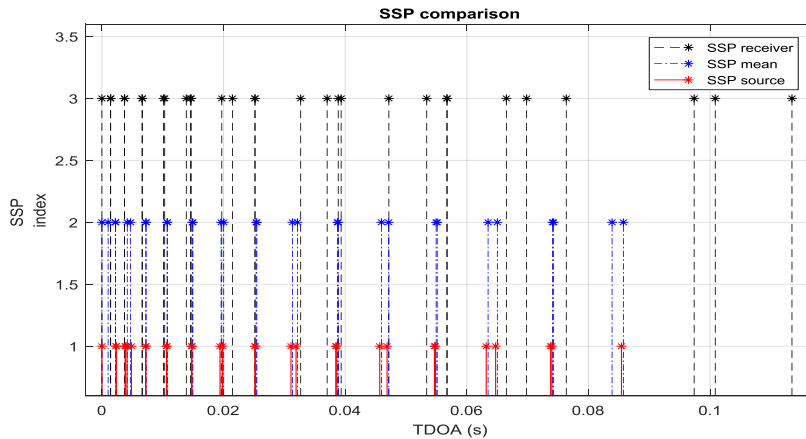


Fig. 30. SSP comparison for true position of the source (9km in range and 56m in depth).

The transmitted signals featuring different narrow and wide-band codes, among which it was considered only the first Linear Frequency Modulations (LFM) with time duration of 2 s (red box at Fig. 31). The center frequency was 5 kHz and bandwidth was 2 kHz (4 KHz to 6 kHz frequency band). The acoustic signals were sampled at 48 kHz. On the top shows the signal on time domain, on the left shows the spectrogram and on the right shows a short FFT varying with time (waterfall graph).

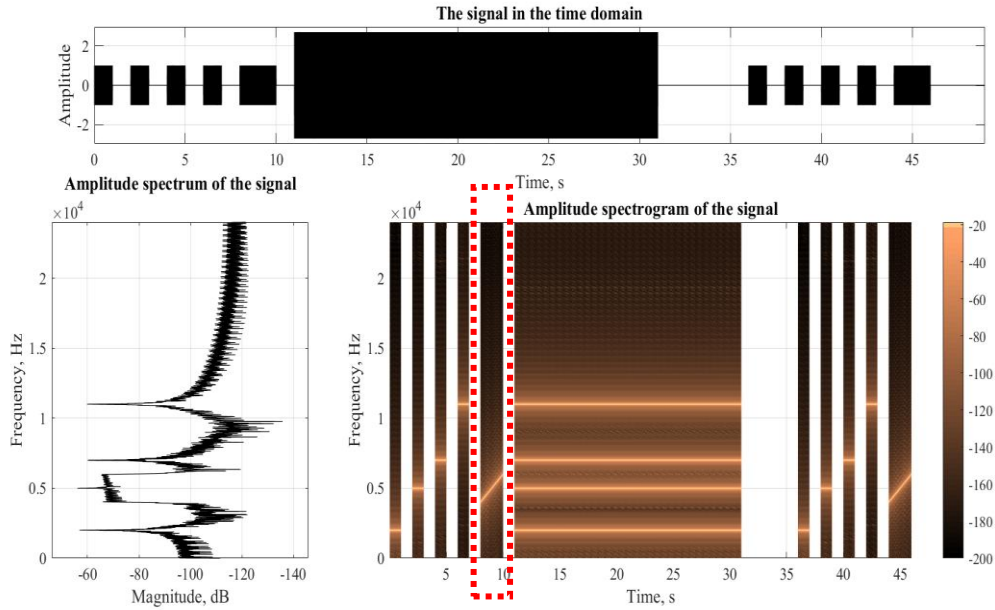


Fig. 31. Transmitted signal used during the experiment. It is composed of short and long pulse signals and LFM, where the red box shows the signal used for the inverse localization.

During the 3-days experiment a total of 415 transmissions (pings) were recorded. The first 100 pings, corresponding to the first 5 hours of the experiment, were chosen to be analyzed due to low variability of the measurement as shown at Fig. 32. These fluctuations can be explained by: the reflection at the wave surface (either constructive or destructive), presence of noise (human noise represented by vessels, and marine noise, animals), and presence of ducts due to a variation of the SSP gradients. A total of 5 pings were eliminated due to a problem at the reception, remaining 95 pings to the analysis. The sea surface was considered calm with roughness about 0.4 m (sea state 0) and no vessels were encountered near the area of the experiment during the first 95 pings. The noise levels suffer variation up to 3 dB between frequencies of 4 to 6 kHz comparing the hydrophone closer to the bottom and the one closer to the surface, and up to 12 dB to low frequencies and close to the surface. Results have shown using the beamforming technique that the first 50 ping are more stable than the remaining 45 pings in term of accuracy to underwater localization. Studies to further understand this variation are still in progress (chapter 6 part B). The SNR has been estimated to be approximately around 11 dB within the frequency band of interest. The level of noise was approximately around -27dB as shown at Fig. 32. Fig. 33 shows the signal recorded by the hydrophone index number 1 during the first ping. The spectrogram on the left figure shows a high level of noise for low frequency.

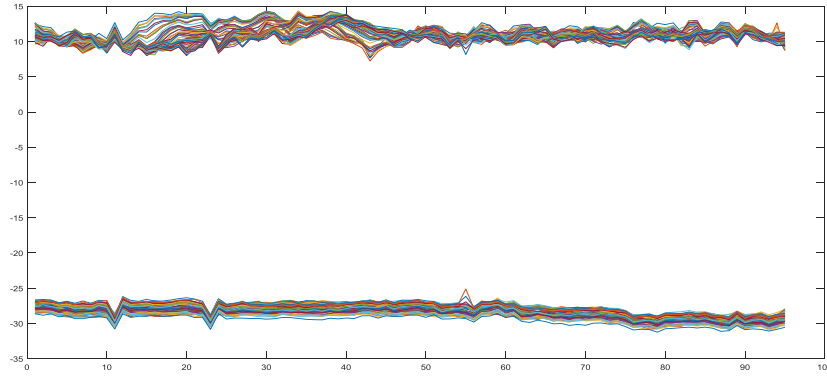


Fig. 32. On the top is the variation of the SNR to all hydrophones and on the bottom is the variation of the noise.

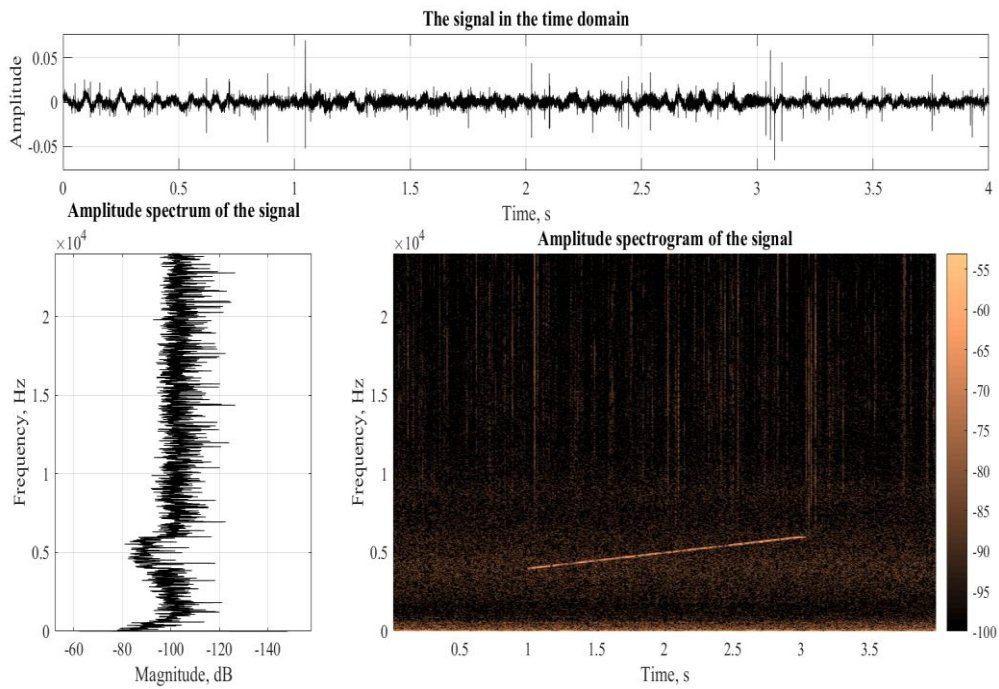


Fig. 33. Received signal on ping number 1 at the hydrophone index 1.

The spatial-temporal of the impulse response of the array, presented at Fig. 34, shows the influence of the multipath effect. The corresponding predicted arrival times are represented by the vertical lines on the time axis, formed by the time delay for each arrival in different hydrophone depths. The yellow dots are the peaks detected after matched filtering. The direction of arrivals (DOA) is extracted from the inclination of these lines follow the equation.

$$\theta = \sin^{-1}(\Delta T \cdot v/d)$$

Where:

ΔT =difference in time from two aligned sensor

V = SPP for the depth of the sensors

D = vertical distance between both sensors in a VLA configuration

The TDOA and the DOA are going to be compared with the ones obtained by simulations and depending of the characteristic of the environment, they are unique associated with a position in space, working as a fingerprint of the propagation channel.

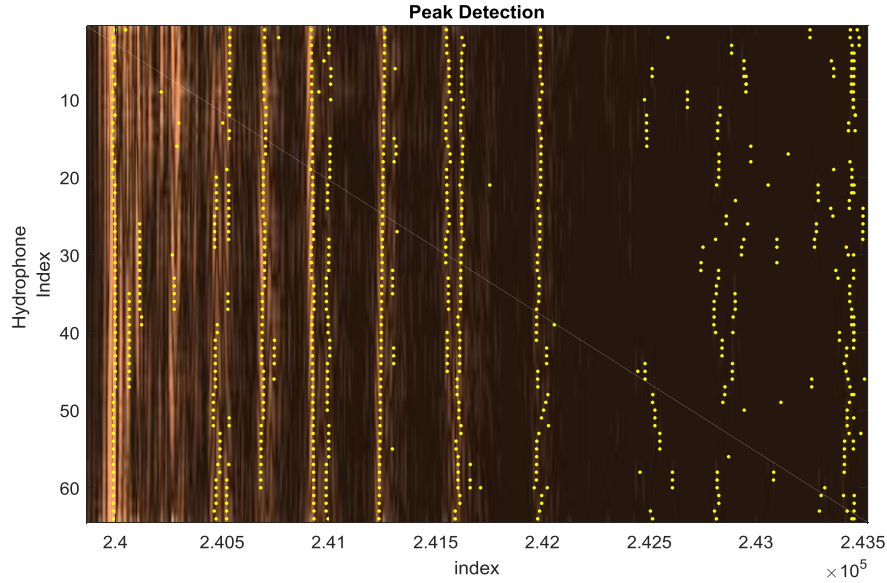


Fig. 34. Received signal on ping number 1 by the array after matched filtering.

5.3. Spatial diversity versus beamforming

The propagation mechanism of shallow water differs from the deep water scenario. In shallow water, most of the multipath suffers one or more reflections, which can be with the bottom, with the surface or a combination of both. Each of these reflections may introduce different: time delays, phase shifts, attenuations, and distortions on the transmitted waveform. These alterations can destructively interfere with one another due to the random superposition of multiple signal paths at the receiver, responsible for a small-scale fading, or constructively given a gain at the aperture of the receiving array. Fundamentally, there are two possible options used as a remedy to this problem, and they differ based on the coherence at each pair of hydrophones.

Spatial diversity is based on the idea of variety, differentness. Hydrophones are placed sufficiently far away from each other so they probably suffer independently fading. Each hydrophone receives a different observation of the same transmitted signal due to a different interference environment on each path. If the receivers are uncorrelated, the probability that multiple paths of the signal are in a deep fade simultaneously is much lower than the probability of a deep fade for a single signal path. Thus the benefit of diversity is the increased reliability of the link between transmitter and receiver.

Beamforming is based on the idea of same signal delayed in time given its direction, where when combined will present a gain. The beamforming allows determining the direction of arrival (DOA) by using the steering vector, assuming plane wave propagation. This is

achieved by combining delayed signals from each hydrophone at slightly different times in such a way that signals at particular angles experience constructive interference (gain) while others experience destructive interference (attenuation).

These processes enable the realization of two types of gain: diversity gain and the beamforming gain, (array gain). These two types of gains are fundamentally different in nature and the final gain of each depends strongly on the channel characteristics, the temporal fading statistics, and the required level of outage probability. [75] Spatial diversity and directivity of the radio channel are contradicting properties. A high degree of spatial diversity implies low directivity and vice versa.

A common space-time statistic is that of the spatial correlation matrix, shown at Fig. 35. The spatial correlation matrix is an important measure of the mutual correlation values of all hydrophone pairs. This measure gives the information of how is the spatial structure of a general channel, meaning how correlate each sensor is with its neighbors.

$$\mathbf{S}_{xx} = E\{\mathbf{S}[n]\mathbf{S}[n]^H\}$$

On the main diagonal, the correlation matrix contains the average channel powers of the antenna elements. The off-diagonal elements specify the complex correlation values between all pairs of antenna elements. For frequency-selective fading channels, the correlation matrix can either be defined for each delay separately or integrated over the delay domain, as shown at Fig. 35 [75]. The position number 48 shows a phase difference due to an inversion of the cable on the sensor.

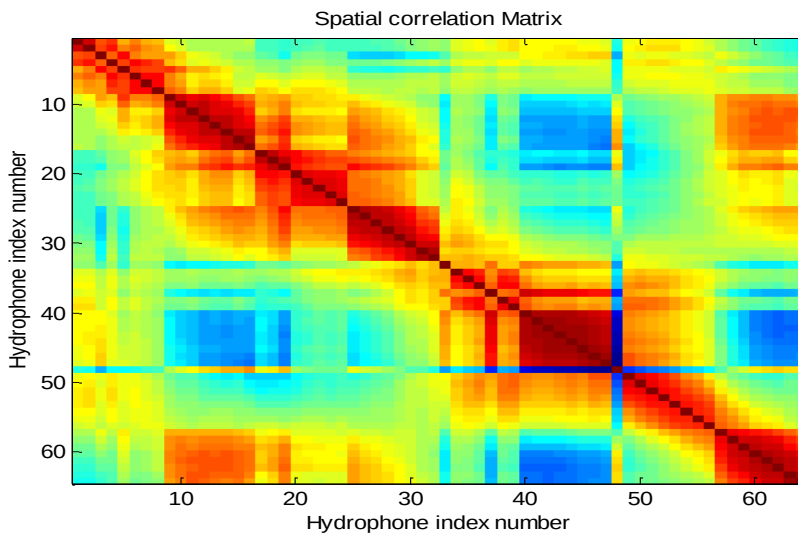


Fig. 35. Average of the spatial correlation matrix over the first 50 pings.

The more diversity the channel offers, i.e. the larger the angular spread, the more diversity gain can be achieved. The more directive the channel is, i.e. narrow angular spread, the more correlated the path are, and consequently the higher array gain is obtained. Both gains depend on the number of antenna elements; however the beamforming is more sensible to this aspect. The key to understand the result of both processes is to analyze the two possibilities when a new hydrophone is added to the array:

- The received signal from the new hydrophone is highly correlated with the others. In this case, the gain from the beamforming will likely be superior, and the reason

is that the signal from a particular path will be combined with the same direction from the others hydrophones while the others directions will not be benefited for any further combinations.

- The received signal from the new hydrophone is highly uncorrelated with the others. In this case, the gain from the spatial diversity will likely be superior compared with the beamforming. The reason is that the new hydrophone will probably have new information. For example a new path that on the others hydrophones were in a fading or a path with an variation in phase that once combined (beamforming) will reduce the energy of the array.

The coherence of the hydrophones also variates with the range, the closer the receiver is from the transmitter the more uncoherent the signals are considering the integration on the time domain due to the high value of the direction of arrival. The larger the receiver array the bigger is the influence of the flat boundaries conditions and the considerations of planar wavefront for using the beamforming due to the linear combination by the steering vector. In this chapter, the results from the spatial diversity will be presented and compared with the results from only use one hydrophone at the receiver. The next chapter the results from the beamforming technique will be presented as well as the comparison with the spatial diversity. Further experiment need to be performed to analyze the Doppler effects and the fully passive configuration (non-cooperative system), where the transmitted signal must be estimated from the received array and applied in both processes.

The process of spatial diversity is defined following three steps:

- 1) Matched filtering the transmitted signal with each hydrophone and detect the peaks, which mean characterizing the impulse response of the channel to each hydrophone (red dots). This step is shown at Fig. 36, limited at 10 hydrophones on a vertical axis to a better resolution, where the red dots represented the arrival time to each hydrophone. Due to the multipath interference some peaks are attenuated, not been detected by the defined threshold and others are detected following a linear shift in time between pairs of hydrophones, associated with the respective angle. These interferences will contribute to the incoherence and coherence respectively of the signal. The modeled TDOA was simulated to each position in range and depth on the grid of simulation for only one hydrophone index number 41 (depth of 56 m). An extrapolation of this result in time was performed given by the DOA to the other hydrophones on the array.
- 2) The Hausdorff Distance (HD) variants are applied hydrophone by hydrophone between the two data set, TDOA measured and TDOA modelled, generating an ambiguity surface to each of them. Fig. 37 shows the corresponding the measured arrival times, represented by the symbol * (red color – measured TDOA sequence) and the modelled TDOA, represented by the symbol * (blue color - modeled TDOA sequence). The Modeled TDOA presented at Fig. 37, was evaluated around 8.2 km in range and the center of the array at 57.5 m in depth. From the same figure it is possible to notice the resemblance between the two patterns. Two marginal direction of the HD was analyzed: first, using the TDOA measured sequence as reference to the HD calculations, forward HD $h(R_t, S_t)$ and the second, using the TDOA modeled data as reference sequence, which is the reverse marginal direction, backward HD $h(S_t, R_t)$. The results from each marginal direction are not symmetric and are based on the number of the TDOA, which

includes extra-point detection or missing point generated by interference effects, as well as due to the temporal resolution to detect the peaks from the measured data. By applying the correct marginal direction it is possible to avoid/reduce the situation of missing point for the comparison, responsible for introducing a high mismatch at the output result.

- 3) Finally, the last step consists of combining all different ambiguity surface generated from each hydrophone. The combination was performed considering 3 different operations: the mean, the median and the maximum of all hydrophones. Each operation presents its own results and will be presented in this chapter.

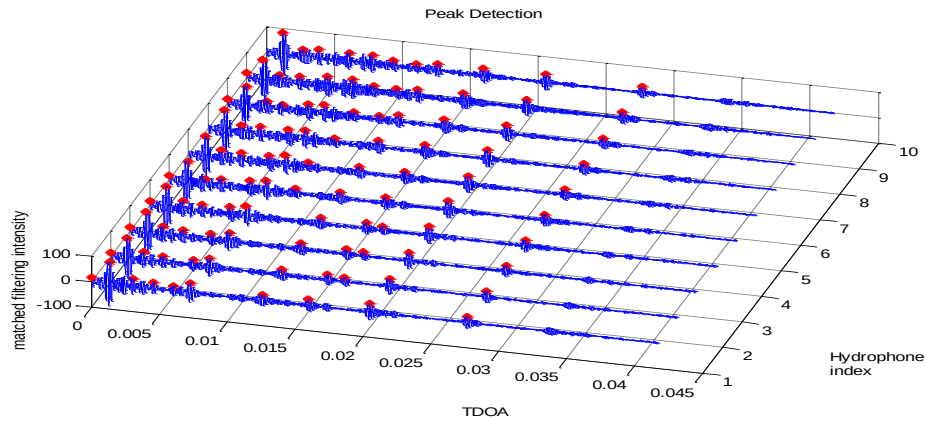


Fig. 36. TDOA detection after matched filtering. The red dots represents the impulse response of the channel.

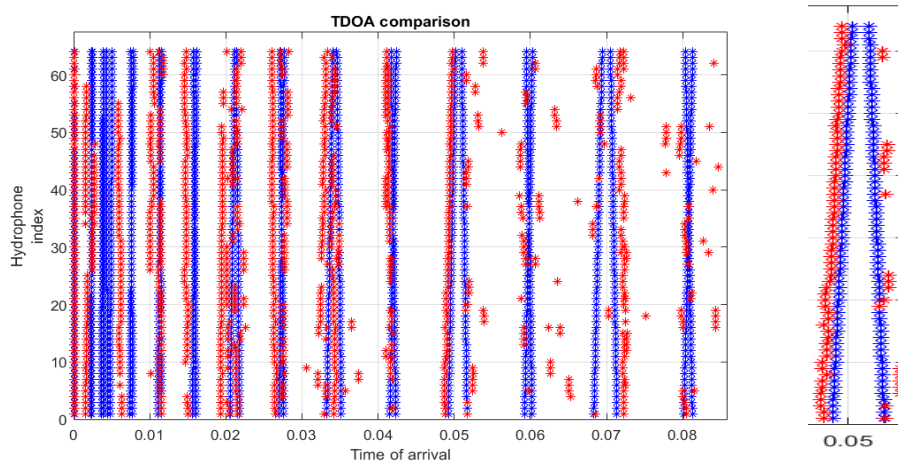


Fig. 37. TDOA peak comparison. Blue (modeled) and red (measured). Ping 3 SSP pinger at 8.2 km. on the right it was plotted a zoom in 0.05s to show the similarity between both TDOA.

5.4. Results with only one hydrophone

The first analysis was performed considering the case of a single receiver. The results of this particular case will be used as reference to more robust processing techniques. Three positions in depth were chosen to perform the HD, the first was the hydrophone index 1, positioned at 62 m depth (maximum depth), the second was the hydrophone index 41, positioned at 56 m depth, same depth used to obtain the TDOA modeled from the Ray path propagation program, and the last one, the hydrophone index 64 positioned at 52.5 m depth (minimal depth of the array). The main propose of this analysis is to compare the influence of

the multipath and noise at different depth. These results will further be compared with spatial diversity and beamforming.

Five variants of HD were used to this analysis. The Maximum Hausdorff Distance (MaxHD Takes the maximum value of discrepancy between the 2 set of TDOA), the Mean Hausdorff Distance (MeanHD evaluates the mean of all variance in time from each path between the 2 set of TDOA), the Median Hausdorff Distance (MedHD takes the median of the vector TDOA variance), the Partial 4 Hausdorff Distance (Part4HD takes the 4 closest variance in time between the 2 set of TDOA) and the Partial -4 Hausdorff Distance (Part-4HD takes all the path less the 4 higher variance in time between the 2 set of TDOA).

The principle of this analysis is the same as presented at the chapter 5 applied on a controlled experiment. However, in a tank, the SSP was constant over range and depth, resulting on a presence of the direct Eigen ray (path with no reflection either at the surface or at the bottom). This path was the one with the higher energy after the matched filtering, obtained by a search for its maximum value and it was used to synchronize both sequences of TDOAs. The HD is sensible to the first element used as reference to the comparison, if there is an even small variance on the first TDOA this error will be propagated to all other elements (see chapter 4). On the Alma experiment, the SSP is not constant, this sound speed variation with the depth will introduce curves on the Eigen paths and after a certain range all paths will have at least one reflection, either with the surface or the bottom or combination of both. The second problem is due to the interference patterns, it is possible that the first Eigen ray is no longer the one with higher energy peak (fading on the first arrival), which would result on wrong position to the reference first element on a TDOA measured after search for the maximum value. It is also possible that due to multipath interferences some of the TDOA in a sequence may completely disappear on noise not being detect anymore, case of missing point on the TDOA recorded (no red lines on fig around 0.04 and 0.06 s).

Fig. 38 shows the comparison with different ranges simulations considering the ping number 3, starting from the position at 7.6 km to 8,2 km and the last one at 9 km. the modeled TDOA represented by the blue lines and the measured TDOA by the red lines. The depth was kept constant at 56m. The SSP used was measured close to the source.

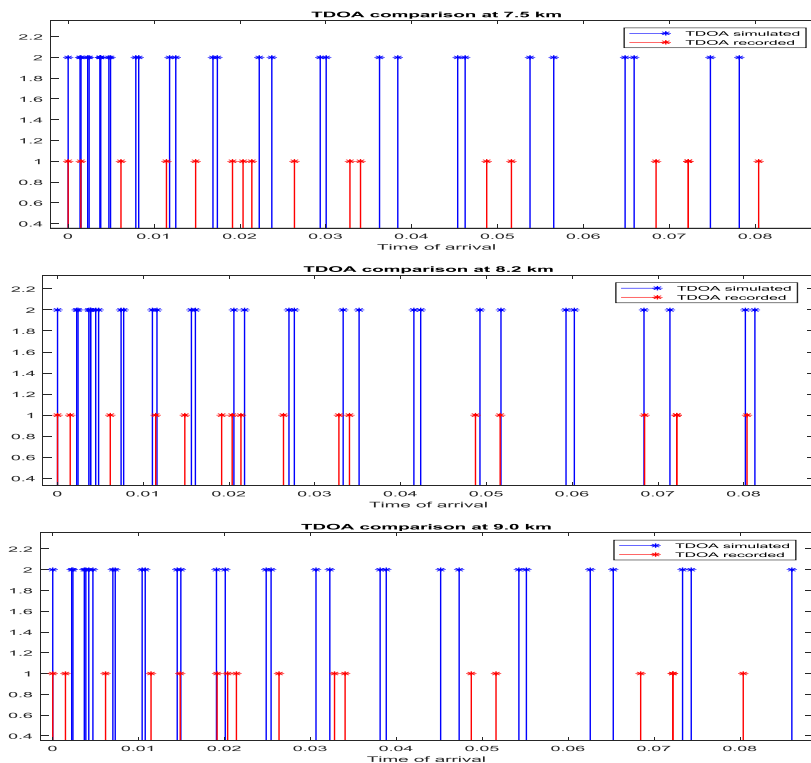


Fig. 38. Blue line TDOA simulated at 8.2 km and 56 m depth using the SSP close to the transmitter, and red line TDOA measured considering ping number 3.

Depending on the direction of HD, the effect of multipath interference is not so severe when appears after the first TDOA and the reason is that the error does not propagates to other elements of the sequences, however with less information because of these missing paths, it can generate more ambiguity points at the output of HD. In general, to avoid missing point problems the sequence of TDOA simulated should have more arrivals than what it was possible to detect on the receiver and should be applied on the defined forward Hausdorff Distance, from the direction received (used as base - less points) to simulated (more points). For example, On the Fig. 38 at the middle, when applied the direct backward HD (one side HD – see chapter 4), from the simulated to the received, the closest points associated with the simulated TDOA around 0.04 and 0.06 s will be at 0.035 and 0.068 s due to the missing point at the received TDOA, resulting in a big mismatch at the output of the HD. To eliminate this problem one possible solution is to apply the forward HD, from the received to the simulated, since that those missing points will not be used to the HD comparison, no red lines to be compared with this particular position.

During the 95 pings, two pings were chosen to be compared on Fig. 39. Ping number 17 and ping number 42. Both cases, the HD were evaluated using the SSP close to the source. The ping number 17 presents a high degree of resemblance compared with the simulation at the range position of 8.2 km and depth of 56 m. In this case, due to the temporal variation of the channel, it was possible to detect the time of arrival close to 0.04 s, different from the ping number 3 (previous case). The last peak detected to the ping number 17 has no close resemblance with the simulation, reason for the MaxHD may fail to localize. The ping number 42 presents a complete mismatch between both TDOA sequences as shown at Fig. 39. The reason for this mismatch is due to the wrong reference to the first position at the measured TDOA used for aligning both sequence. In this case, the error will be propagated to all the remaining sequence, resulting in a wrong localization position. Fig. 39

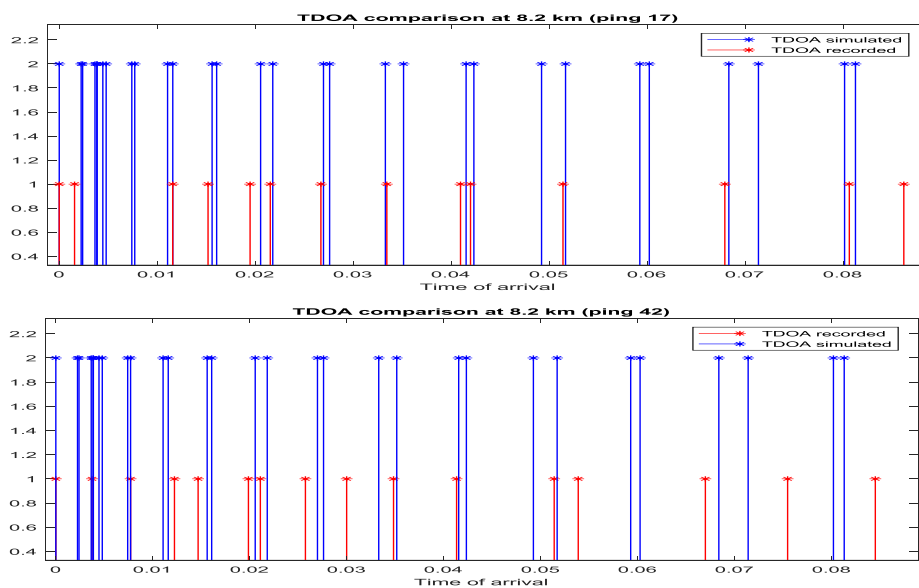


Fig. 39. B

Blue line TDOA simulated at 8.2 km and 56 m depth using the SSP close to the transmitter, and red line TDOA measured: ping number 17 (top) and ping number 42 (bottom).

Fig. 40 shows the output to the five different HD. As expected the ping number 17, due to the last arrival time on the measured signal, presents a big mismatch on the MaxHD, however the Mean, Median and Partial4-HD, presents a detection in range close to the correct source position. By only considering 4 closest elements (Partial4HD), the uniqueness information of the sequence was lost given more ambiguity, leading to a wrong detect position. The analysis of the ping number 42 was expected that all different HD variants would be unable to correct locate the source due to its initial reference mismatch.

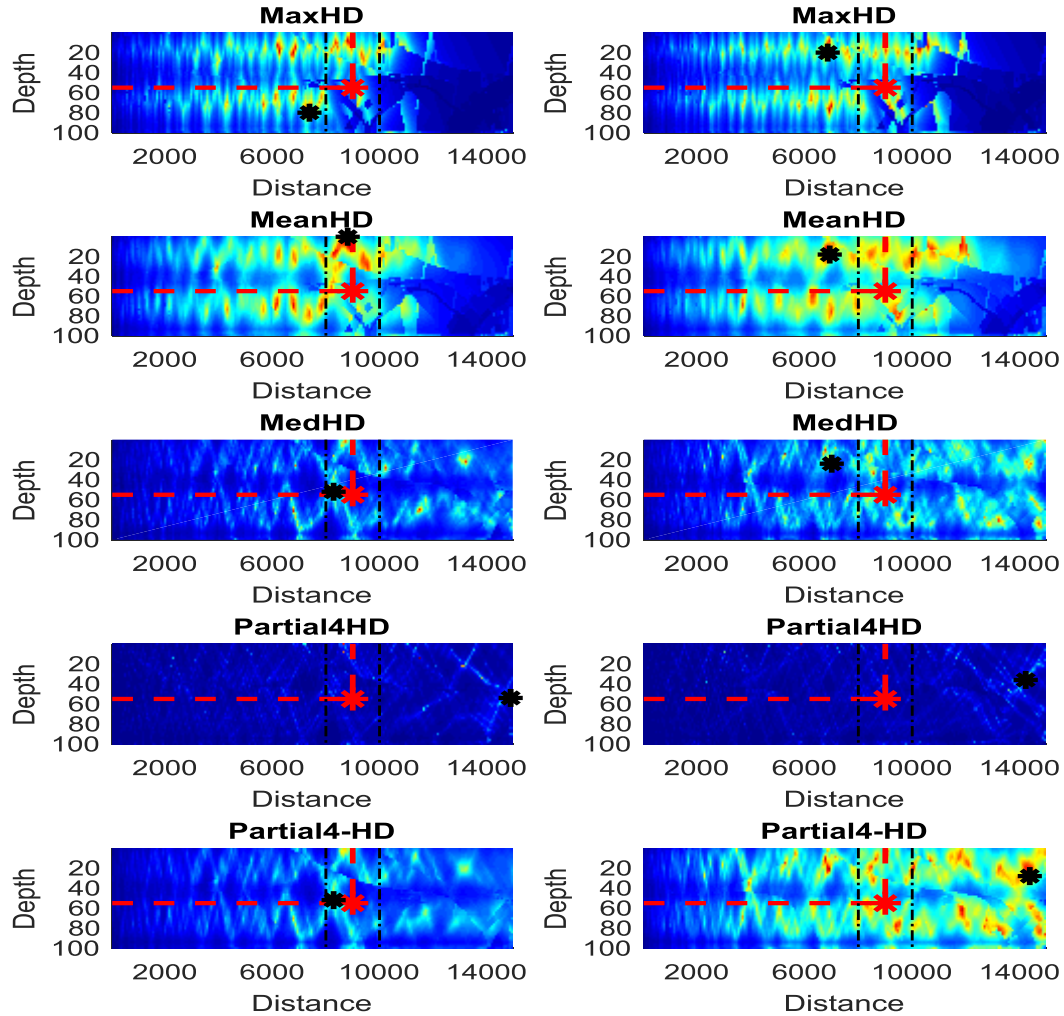


Fig. 40. Output to five diferent HD variants: ping number 17 (left) and ping number 42 (right).

In order to summarize the results for each HD variant applied on each on of 4 different SSP, a table containing the number of detection, both in range and depths is presented. According to operational navy specialist, one considers localization as sufficiently correct when the error is less than 20% of the target position (True target location: range 9 km and depth 56 m). The amount of accept error adopted in this work was: up to 1km in range and up to 10 m in depths, which is around 10% around the correct target location. Only two SSP will be presented in this chapter: the first one being measured close to the source, and the second measured close to the receiver, both simulated by the program RAMSES at Thales. The two remaining simulations, SSP close to the source simulated by a **second program** and using the SSP evaluated by the mean between the two measured, can be found on the appendix E.

Table number I and II shows the results for the SSP close to the source simulated by the RAMSEAS ray path propagation (THALES). On the first column is presented the depth of each isolated hydrophone used for comparison. The HD was applied on the first 95 pings.

Table I .Percentage of pings detected inside the limit of error from the true position (both same position error equal to 0) up to 1 km in range and 10 m in depth. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to the simulated** to avoid the missing point. (True solution: range 9 km; depth 56 m)

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	28%	23%	24%	17%	24%
56m	39%	26%	23%	24%	18%
62m	40%	44%	25%	31%	5%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	2%	2%	14%	8%	24%
56m	4%	7%	11%	12%	29%
62m	8%	8%	20%	9%	14%

Table II. Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth from the reverse direction, from **simulated to the received**.

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	19%	22%	26%	29%	21%
56m	20%	22%	31%	26%	16%
62m	23%	31%	32%	33%	5%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	56%	64%	35%	45%	25%
56m	44%	56%	24%	37%	36%
62m	39%	51%	22%	33%	16%

From the results of table I and II, The two first variants (MaxHD and MeanHD), presented a better result in range when applied to the direction from the received to the simulation (28% and 23% versus 19% and 22% respectively) due to the problem of missing points at the received data, however the remaining variants due to its combinations and the removal of big mismatch, presented a better result considering the direction of simulated to the received. The best result in depths was found using the direction of simulated data to the received. Overall, when only one sensor is used, the elimination of some elements in a TDOA sequence (less information), especially the case of Partial4HD, tends to reduce the precision of the localization. This situation will be further analyzed by using the spatial diversity.

Table number VII and VIII shows the results for the SSP measured close to the receiver. The simulation was performed by the RAMSES (THALES).

Table III .Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth. The **SSP used was measured close to the receiver** and the HD was applied from the direction of **received to the simulated** to avoid the missing point. (True solution: range 9 km ; depth 56 m)

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	45%	53%	43%	52%	29%
56m	44%	44%	36%	46%	16%
62m	44%	53%	42%	47%	20%
% detetion in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	13%	22%	24%	24%	8%
56m	17%	21%	13%	26%	27%
62m	19%	36%	33%	39%	34%

Table IV. Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth from the reverse direction, from **simulated to the received**.

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	1%	3%	3%	0%	16%
56m	0%	4%	3%	0%	8%
62m	0%	0%	12%	0%	37%
% detetion in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	1%	3%	6%	0%	28%
56m	0%	1%	6%	0%	52%
62m	0%	0%	5%	0%	38%

Overall the different SSP, the results for using a single hydrophone presents a better accuracy in range than in depths when performed from the direction of received to the simulated, being in average able to detect 40% of the total 95 pings. The best accuracy in depth came from the direction from simulated to the received. The best result to the depths was found using the SSP calculated by the mean between both SSP measured (close to the source and receiver), at the depth of 52.5m using the MeanHD, able to detect 73% of the pings (appendix E). The depths localization was found to be more sensible to variations of the SSP, where using the SSP measured close to the receiver was unable to locate even one correct depth in 3 of 5 HD variants for the depth of 62 m.

5.5. Results with Array - Spatial diversity

It was explained that the signal transmitted from the source reaches each sensor along a cluster of multipath arrivals with different energies, and very close arrival time delays and angles, resulting in overlaps and interference. These small variations in time and/or angle can generate an ambiguity location either in target range or in depths, especially when the interference occurs at the first arrival in time used to synchronize all the remaining sequence. The spatial diversity among the hydrophones of the quite long array (10 m) is used as a remedy against those interferences. The main idea consists of positioning several hydrophones in different locations, in the ALMA experiment equally spaced in depth (0.15m). Depending of the spacing between them, the signal recorded experiences different interference pattern resulting in fading, which in an uncoherent system has high probability of occurrence in different time.

Eight variants of HD were used to this analysis, the five previously used to the case of only one hydrophone, plus the Partial-2 Hausdorff Distance (Part-2HD takes all the path less the 2 higher variance in time between the 2 set of TDOA), the Partial-1 Hausdorff Distance (Part-1HD takes all the path less the higher variance in time between the 2 set of TDOA). These variants eliminate the higher difference (maximal mismatches) between the 2 sequences, which can occurs due to extra-points detection (wrong detection). On Fig. 41, hydrophone index 9 presents the case of extra-points detection on the arrival close to 0.03s (black arrow), this maximal value of error will be eliminated by using these variants. **The last variant was performed by the probabilistic formulation HD, where the HD combinations will be fitted in a probability density function (see chapter 4).**

On Fig. 41 (black ellipse), the blue dots are the TDOA simulated and the red dot the TDOA measured. Hydrophone index number 7 at the arrival time close to 0.015 s is in a presence of fading, not being detected (red dot), the subsequent hydrophones due the small spacing between them also experiences similar interference pattern (coherence between close hydrophones), however as the spacing between hydrophones increases, the hydrophones start getting uncoherent due to the different combination of multipath and the time of arrival starts being detected. Since that those interference occurs in different times and different depths, the combination of all hydrophones should reduce the ambiguity generated by the interferences and fading, improving the target localization. The second and most important benefit of using spatial diversity is to define the first arrival used as reference to all HD comparison. The process is the same as applied to a single hydrophone. A matched filtering with the transmitted signal is applied to each hydrophone, the search for the maximum value is performed and the first detected position associated with a hydrophone index will be positioned as the reference time zero. At the simulated TDOA the first arrival of the same hydrophone index from the received sequence is placed at the reference time zero. This correction at the simulated TDOA is important in cases of the high value to the first angle of arrival due to the inclination in time generated by this angle. In the ALMA experiment, the first angle was 0.6° to the correct position, so this correction at the TDOA simulated was disregarded. After this process the HD can be applied as discussed at chapter 4.

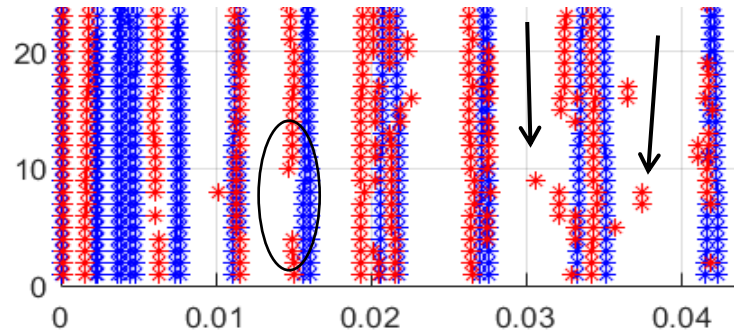


Fig. 41. TDOA comparison. Blue dots - TDOA modelled, red dot - TDOA measured. Vertical axis represents the hydrophone index and the horizontal axis represents the TDOA.

Fig. 42 shows the similarity of the output of the MaxHD to the hydrophone index 1 to 2 and index 63 to 64 (spacing of 0.15cm between hydrophones - coherence) and the dissimilarity between the hydrophone index 1 to 64 (spacing of 9.45m between hydrophones - decoherence). The effect of those ambiguity points can be reduced by evaluating the combinations of all different hydrophones as presented on the previous section. Three combinations were evaluated to each HD variant. The first result came from using the mean of the HD output from all Hydrophones. The mean of all hydrophones was choose to be presented due to its stability overall different SSP. The second result was evaluated by the median of all hydrophones. And the last, performed by the maximum HD output presented by all hydrophones. These two last combinations at some configurations presented the best localization results however due to its high instability of the target results over different configurations it was decided not to be shown.

The last improvement came from using spatial filtering after the array combination. The TDOA at different hydrophones index should follow a linear time delay distribution given its DOA, however as seen on Fig. 37, the detected TDOA suffer a small variation in time from its linearity give its direction of arrival. This variation in time could be resulted from the temporal resolution of the peak detection given the different multipath interference as well as due to the roughness either at the surface (sea wave) or at the bottom (approximation to a flat configuration). Due to the spatial proximity properties of the HD, these variations in time results in a defocusing of the HD output, where a small-time variation will be responsible for a small variation at the position of the target, distributing the final position of the average HD output to its neighborhood. The solution to this problem consists of applying a spatial filtering with a defined window size to consider the information of the located target's neighborhood. The spatial filtering also reduces the effect of high value of ambiguity points. Five different kernels were used with different window size: A squared window was used with size variation from 3-by-3 to 10-by-10 to the first four different kernels: Mean, circular mean (Disk), Gaussian and Median. The last kernel used was the Wiener with a window size variation from 6-by-6 to 12-by-12. To synthesize the results only the best overall spatial filtering will be presented, which will be compared with the results of not using the spatial filtering (No S. Filter).

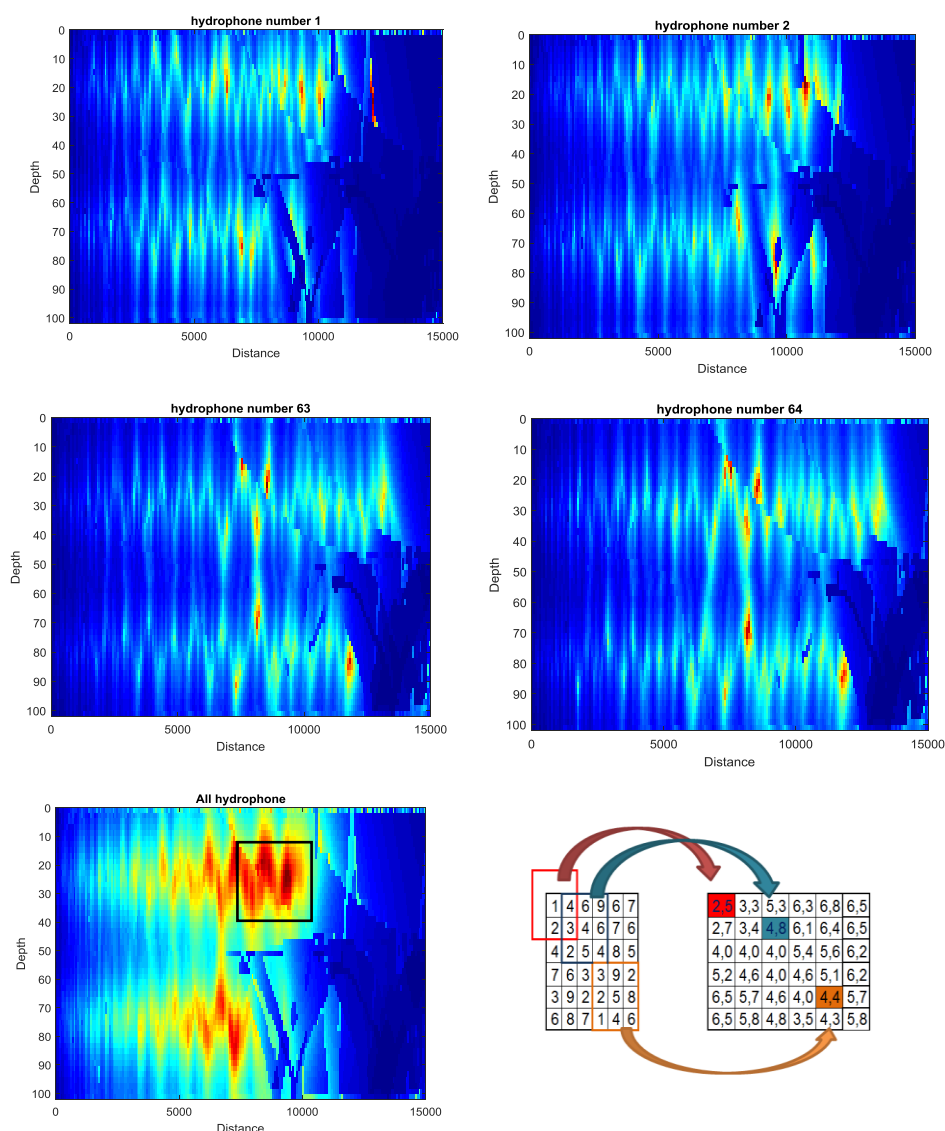


Fig. 42. Output of the MaxHD to each isolated hydrophone index and the final result from the combination of all 64 hydrophones. I don't know how to improve this figure

Two SSP will be presented here, the SSP close to the source and the SSP close to the receiver, considering the direction of received to simulated. The last two remaining SSP results can be found on the appendix F. Each SSP generated its own TDOA simulated sequence which was compared with the same the TDOA received sequence extracted from each hydrophone, thus the different target detection results came from the different input parameters at the simulations.

5.5.1 SSP close to the source

The Fig. 43 shows the output of the HD to the main variants applied on the 64 array for the ping number 1. The first column was performed with the average of the 64 hydrophones using no spatial filtering and the second column using the spatial filtering disk with window size of 9-by-9. The true source position is represented by the pink symbol “*” located at the intersection of the red lines at 9km in range and 56 m in depths. The black symbol “*” represents the target’s locations for each one of the HD variants.

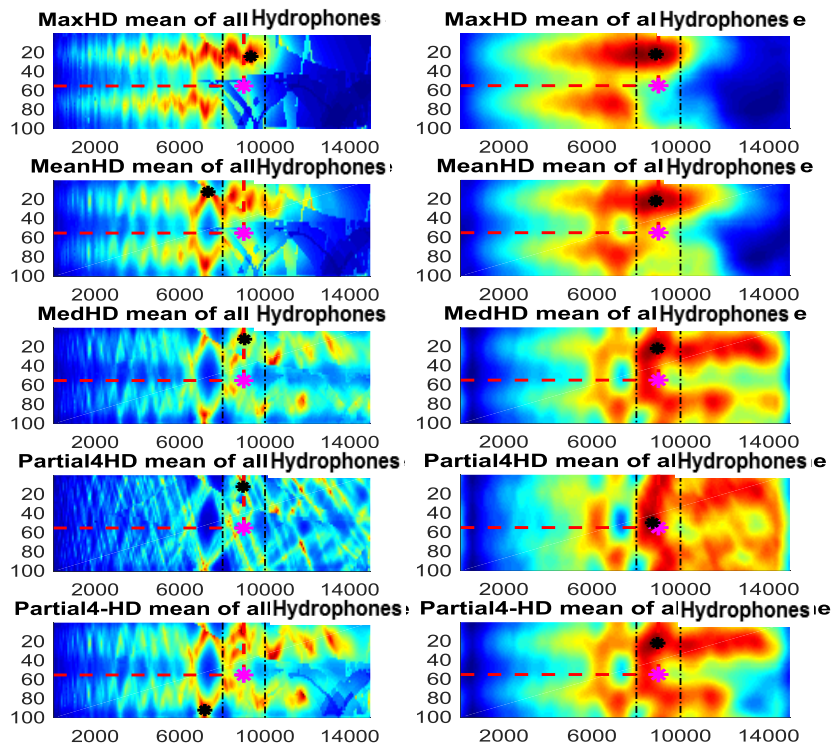


Fig. 43. Output of the mean 64 hydrophones array to the main HD variant evaluated to the ping number 1.

The HD variants were evaluated using a variation of the array size starting from 64 hydrophones to 1 hydrophone. These tables will be used to define the minimal number of hydrophones to futures measurements given the requested minimal value of error accepted. A total of 95 pings were processed.

Table I .Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to the simulated** to avoid the missing point.

% detection in range with accepted error up to 1km (SSP close to the source)									
HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	88%	82%	56%	42%	65%	73%	77%	97%
	SF-disk 9	86%	99%	88%	41%	99%	100%	100%	100%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	91%	78%	57%	45%	65%	73%	75%	91%
	SF-disk 9	84%	99%	86%	41%	98%	100%	100%	100%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	82%	78%	55%	44%	64%	71%	74%	91%
	SF-disk 9	80%	99%	79%	37%	95%	99%	100%	100%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	72%	76%	54%	44%	60%	71%	73%	80%
	SF-disk 9	76%	99%	80%	33%	92%	100%	100%	99%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	62%	71%	53%	39%	61%	71%	69%	71%
	SF-disk 9	75%	94%	65%	32%	83%	96%	95%	94%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	62%	63%	45%	31%	53%	63%	63%	63%
	SF-disk 9	77%	89%	51%	21%	68%	83%	88%	87%
1 Hydrophone (hydrophone 1 - 62m)	No S. Filter	40%	44%	25%	5%	31%	41%	45%	44%
	SF-disk 9	66%	72%	28%	3%	39%	48%	58%	61%
% detection in depth with accepted error up to 10m (SSP close to the source)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	2%	31%	24%	33%	32%	21%	15%
	SF-disk 9	0%	0%	1%	48%	0%	0%	0%	0%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	3%	29%	18%	32%	33%	21%	20%
	SF-disk 9	0%	0%	2%	51%	0%	0%	0%	0%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	4%	24%	17%	29%	29%	18%	24%
	SF-disk 9	0%	0%	3%	49%	0%	0%	0%	0%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	6%	24%	13%	23%	28%	19%	29%
	SF-disk 9	0%	0%	2%	39%	1%	0%	0%	0%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	2%	8%	17%	20%	18%	26%	18%	32%
	SF-disk 9	0%	0%	2%	40%	2%	0%	0%	0%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	4%	9%	21%	26%	24%	28%	20%	26%
	SF-disk 9	0%	0%	2%	29%	2%	0%	0%	4%
1 Hydrophone (hydrophone 1 - 62m)	No S. Filter	8%	8%	20%	14%	9%	9%	9%	16%
	SF-disk 9	0%	0%	5%	18%	1%	0%	0%	1%

The histogram of the best HD variant (Partial-1HD to this SSP) is presented on Fig. 44. The left plot shows the improvement of using only 1 hydrophone (blue color) to the case of using an array with 64 hydrophones (red color). The right plot shows the improvement of using the array with 64 hydrophones without Spatial filtering (blue color) to the case of using SF with kernel disk with window size of 9-by-9 (red color). The mean and the standard deviation of the results in range and in depths were also evaluated by the function `evfit` in MATLAB. The blue and red dashed lines represent the extreme value probability density function evaluated by the function `evpdf` in MATLAB, which used the value of μ (green dotted line) and σ from the previous MATLAB function. The black dashed line represents the true source location. The bottom plot shows the variation of the detected range compared with the true target location (black line at 9km): using only 1 hydrophone (blue line), 64 hydrophones with NO-SF (red line) and using SF-disk-9 (green line). The symbol “*” indicate when the detected range is outside of the limit error accepted of 1km (black dashed line to each direction from the true target location), varying to the total number of ping on the X-axis.

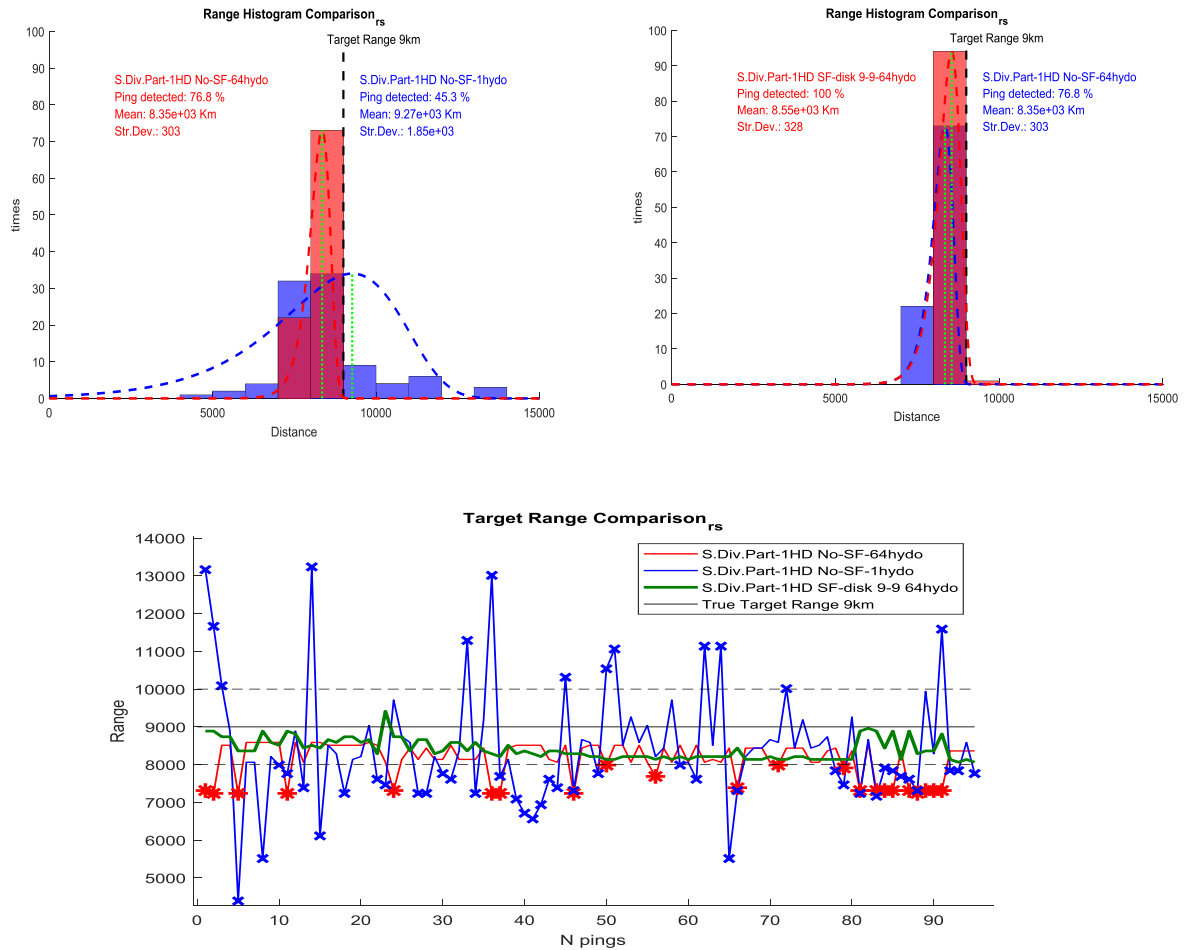


Fig. 44. Histogram of the Partial-1HD applied to range localization (top) and detected range variation compared with true target location.

A similar process is shown at Fig. 45, using the same HD variant (Partial-1HD to this SSP), however now applied to the depths localization at 56m. In this case for the only one hydrophone, the value of detected depth is distributed overall depths (left histogram). When applied on 64 hydrophones, most of the detected depths occur at a depth up to 20 m. By using the filtering disk 9-by-9, it was found a more stable result, where most of the detections were at $20 \text{ m} \pm 5 \text{ m}$. On the bottom plot showing the variation of the detected depths with the ping number, it is possible to see the high fluctuation of the results for the case of not using filtering (red and blue color), and the more stable results when using the spatial filtering (green color). The final result however presents a bias regarding the true target location at 56m depth.

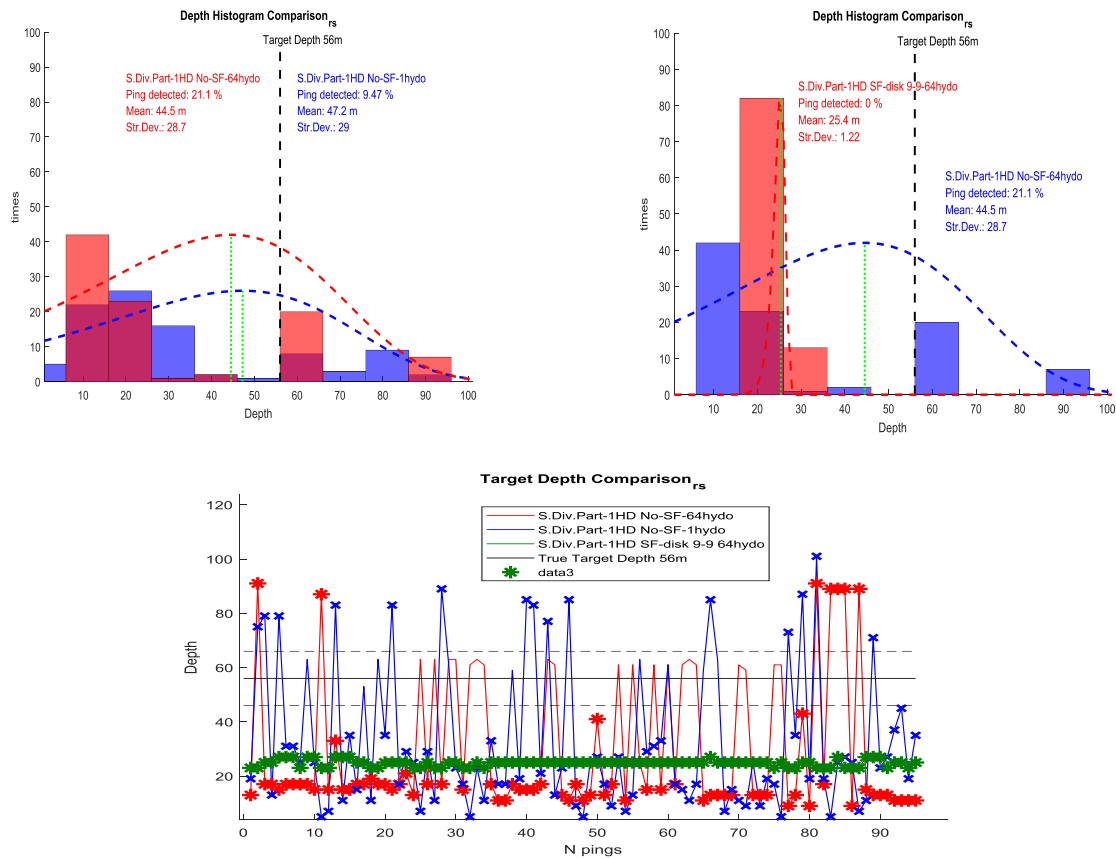


Fig. 45. Histogram of the Partial-1HD applied to depth localization (top) and detected depth variation compared with true depth location..

5.5.2 SSP close to the receiver

During all the analysis on the previous SSP results, the best and more reliable results from the spatial filtering came from the kernel disk with the window size 9-by-9, however the same kernel present a worst result when applied on the SSP close to the receiver. The reason from this disparity is shown at the Fig. 46 and Fig. 47. Keeping the range fixed at 9 km and varying the depths from 0 to 100m, the SSP close to the receiver, presents discontinuities of the linearity on the simulated arrival time. These variations of the arrival time with depths

introduce at the output of the HD a noise effect (defocusing of the ray paths). The pattern of the SSP close to the source generates at the output of the HD a defined ray path, shown at Fig. 47 on the right. These ray paths are not identified on the SSP close to the receiver due to the noise effects. The wiener kernel is known on the image processing for reducing the influence of the salt and pepper noise effects, and the best result was obtained with the window size 11-by-11.

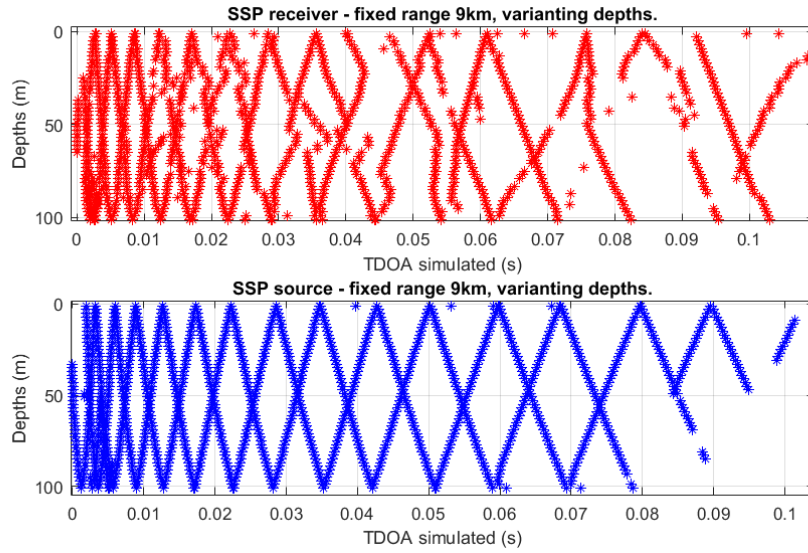


Fig. 46. Variation in depths of the arrival time with a fixed range at 9km to the SSP close to the receiver (top) and to the SSP close to the source (bottom).

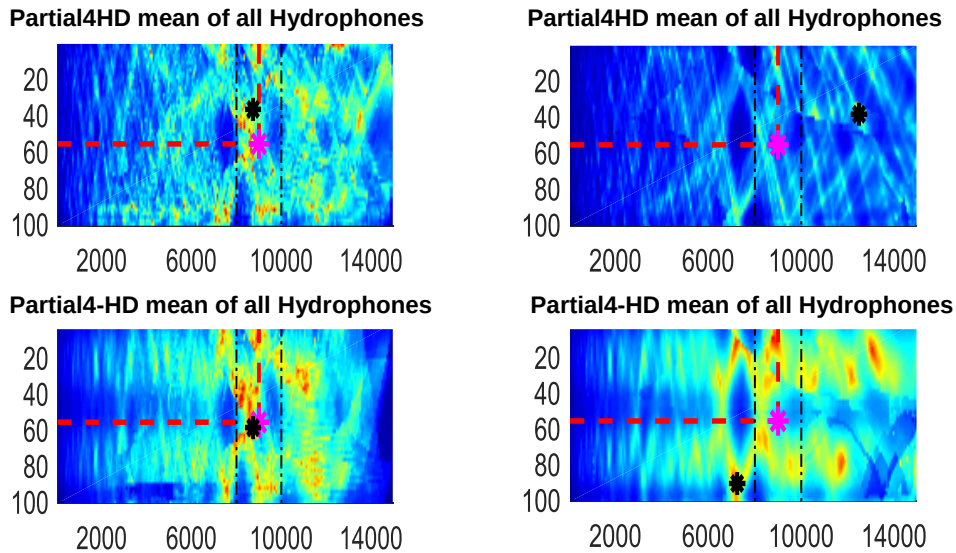


Fig. 47. Output of the HD to the ping number 2 with 64 array sensors, applied to the SSP close to the receiver (left) and to the SSP close to the source (right).

The Fig. 48 shows the output of the HD to the main variants applied on the 64 array for the ping number 1. The first column was performed with the average of the 64 hydrophones using no spatial filtering and the second column using the spatial filtering wiener with window size of 11-by-1, used to smooth the output of the Hausdorff distance. The true source position is represented by the pink symbol “*” located at the intersection of the red lines at 9km in range and 56 m in depths. The black symbol “*” represents the target’s locations for each one of the HD variants. The noise effect could be reduced as well as the ambiguities on the output of the HD. The results from the HD using the SSP measured close to the receiver presents a better accuracy in depths locations.

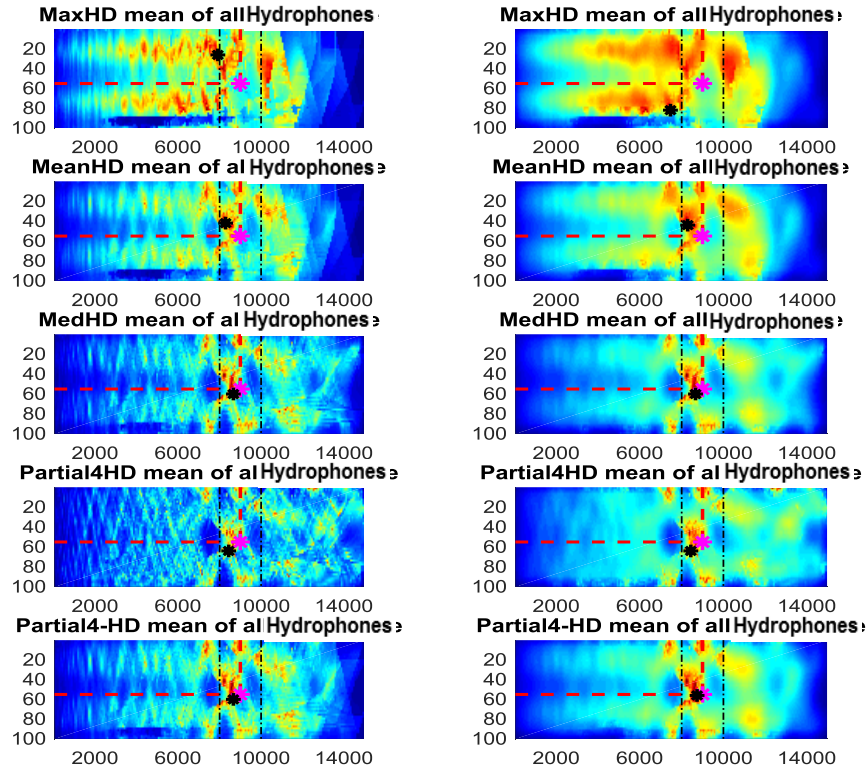


Fig. 48. Output of the HD variants to the ping number 1 to the 64 array sensors: mean of 64 sensors (left), median of 64 sensors (middle) and maximum of 64 sensors (right).

The results of the second SSP, measured close to the receiver, is presented on table V. As the number of hydrophones decreases, high value of ambiguity appears leading to a loss of precision. The bold results represent the best value for each line, which helps to identify the best variant (column), as well as the comparison between the use of SF and not using SF.

Table V .Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth. The SSP used was measured close to the receiver and the HD was applied from the direction of received to the simulated to avoid the missing point.

% detection in range with accepted error up to 1km (SSP close to the receiver) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	21%	83%	87%	53%	92%	89%	91%	76%
	SF-Wiener 11	9%	89%	93%	62%	97%	92%	94%	94%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	24%	83%	89%	53%	92%	89%	88%	80%
	SF-Wiener 11	12%	91%	93%	60%	94%	91%	92%	95%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	28%	85%	85%	52%	93%	89%	91%	79%
	SF-Wiener 11	19%	88%	92%	58%	95%	88%	89%	94%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	38%	82%	79%	59%	85%	88%	88%	79%
	SF-Wiener 11	27%	83%	86%	61%	91%	91%	89%	87%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	38%	76%	71%	51%	82%	84%	82%	76%
	SF-Wiener 11	37%	77%	77%	55%	81%	82%	83%	80%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	45%	60%	54%	33%	66%	60%	63%	62%
	SF-Wiener 11	41%	64%	58%	34%	66%	69%	69%	64%
1 Hydrophone (hydrophone 1 - 62m)	No S. Filter	44%	53%	42%	20%	47%	60%	55%	55%
	SF-Wiener 11	40%	48%	48%	19%	55%	63%	54%	45%
% detection in depth with accepted error up to 10m (SSP close to the receiver)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	8%	39%	58%	25%	60%	54%	44%	43%
	SF-Wiener 11	2%	17%	41%	23%	43%	25%	20%	23%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	7%	34%	59%	28%	64%	55%	41%	45%
	SF-Wiener 11	3%	18%	44%	25%	41%	26%	19%	26%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	9%	34%	56%	28%	60%	53%	48%	49%
	SF-Wiener 11	3%	14%	43%	29%	46%	25%	23%	32%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	15%	38%	52%	35%	56%	54%	51%	43%
	SF-Wiener 11	8%	20%	40%	29%	42%	38%	34%	32%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	8%	32%	41%	43%	51%	48%	46%	45%
	SF-Wiener 11	13%	17%	37%	38%	38%	35%	28%	28%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	14%	32%	31%	35%	42%	38%	33%	29%
	SF-Wiener 11	21%	20%	29%	40%	33%	28%	29%	26%
1 Hydrophone (hydrophone 1)	No S. Filter	19%	36%	33%	34%	39%	39%	40%	27%
	SF-Wiener 11	14%	28%	31%	32%	39%	38%	34%	25%

The histogram of the best HD variant (Partial-4HD to this SSP) is presented on Fig. 49. The left plot shows the improvement of using only 1 hydrophone (blue color) to the case of using an array with 64 hydrophones (red color). The right plot shows the improvement of using the array with 64 hydrophones without Spatial filtering (blue color) to the case of using SF with kernel wiener with window size of 11-by-11 (red color). The mean and the standard deviation of the results in range and in depths were also evaluated by the function `evfit` in MATLAB. The blue and red dashed lines represent the extreme value probability density function evaluated by the function `evpdf` in MATLAB, which used the value of μ (green dotted line) and σ from the previous MATLAB function. The black dashed line represents the true source location.

The bottom plot shows the variation of the detected range compared with the true target location (black line at 9km): using only 1 hydrophone (blue line), 64 hydrophones (red line) and using SF-disk-9 (green line). The symbol “*” indicate when the detected range is outside of the limit error accepted of 1km (black dashed line to each direction from the true target location), varying to the total number of ping on the X-axis.

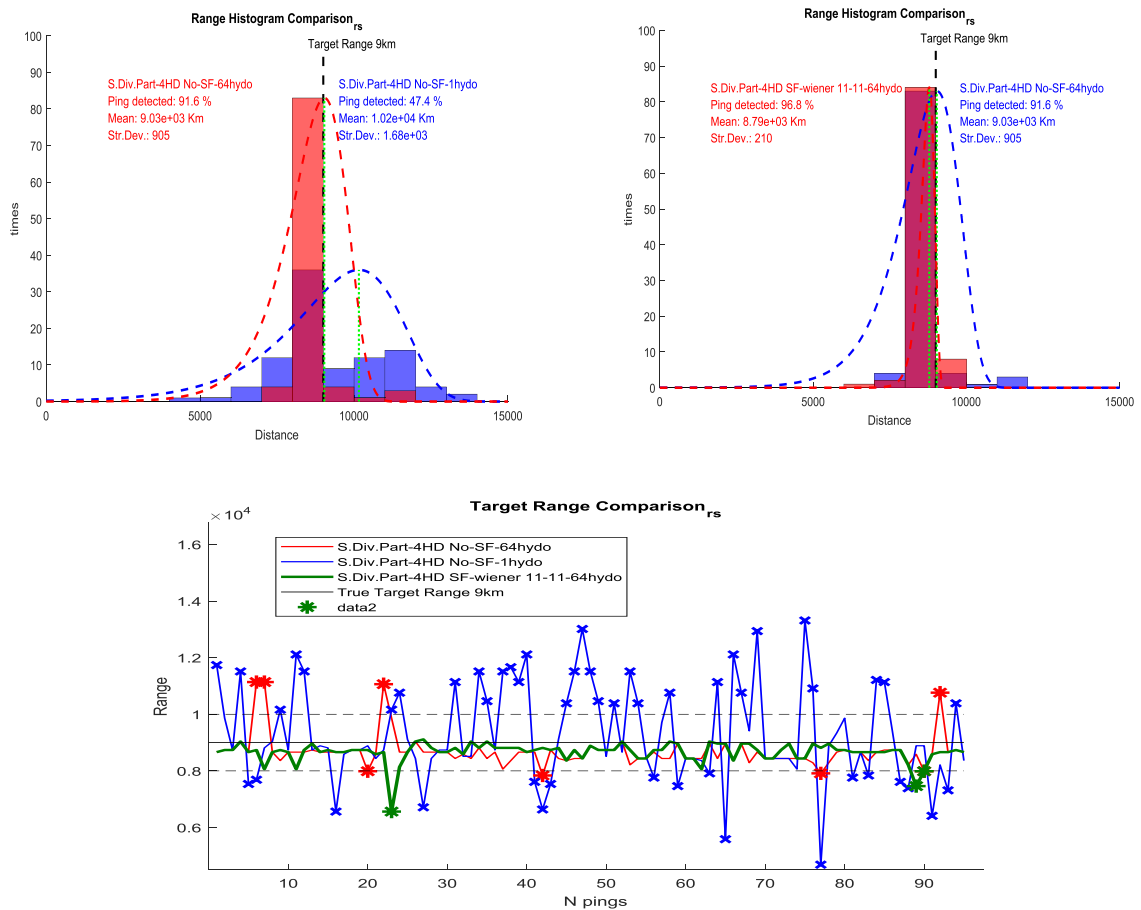


Fig. 49. Histogram of the Partial-4HD applied to range localization (top) and detected range variation compared with true target location.

A similar process is shown at Fig. 50, using the same HD variant (Partial-4HD), however now applied to the depths localization at 56m. By using the SSP close to the receiver was able to correct located 60% in depths (error of 10 m to the true source at 56 m depth) of the total number of pings.

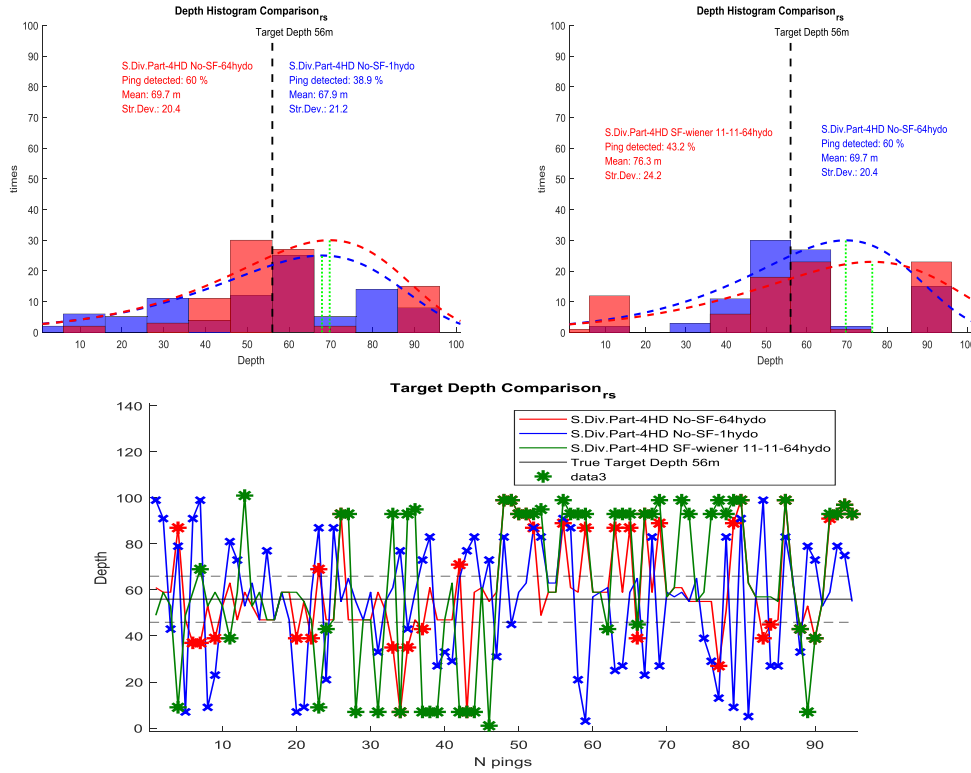


Fig. 50. Histogram of the Partial-4HD applied to range localization (top) and detected range variation compared with true target location.

5.6. Best Configuration

Overall HD variants the most consistent over all 4 SSP was the Partial-2HD. The range variation of each SSP is presented on Fig. 51. The best SSP was obtained using the SSP close to the source simulated by the program RAMSES (blue line) where all the pings were inside the accept limit of error of 1km. the second best result was found using the SSP close to the source simulated by the second ray path program (X.program) with 4 ping out of the 1km interval (red line). The next SSP was measured close to the receiver with 8 pings out of the 1km. the last SSP was performed by the mean of the 2 measured SSP. By using the same HD variant (Partial-2HD) the SSP mean presented 12 pings located outside the limit of 1km in range. When increase the accepted limit of error of to 2km (around 20% of the target location) only the SSP mean detect a total of 4 pings out of this new range interval. The detected depth evaluated for the 4 SSP was not plotted due to the bias compared with the true source.

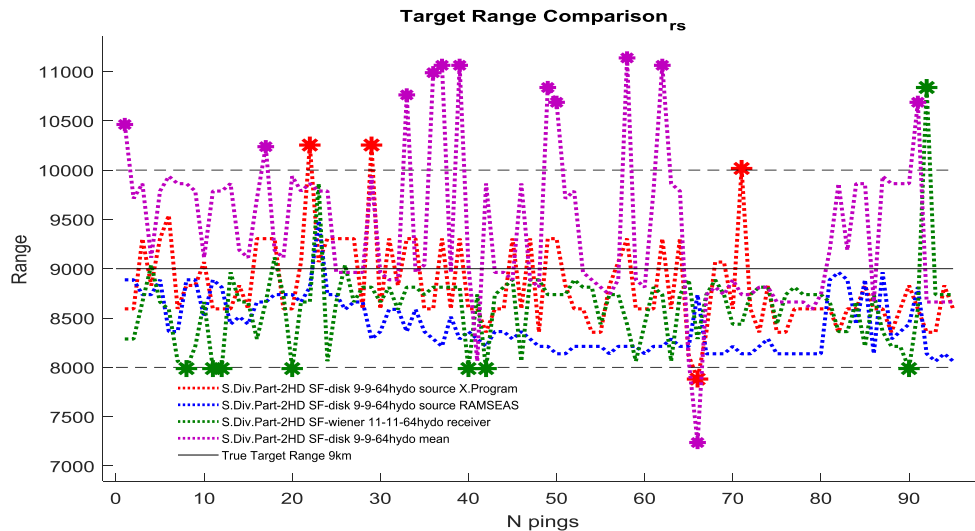


Fig. 51. Detected range variation compared with true target location using the Partial-2HD evaluated to the 4 SSP.

5.7. Minimal number of Hydrophones.

The 8 hydrophones array in both SSP after applied the spatial filtering are still able to correct localize more than 90% of the total amount of transmitted pings. The minimal number of hydrophones to an accuracy of more than 80% of the ping after the spatial filtering is 4 hydrophones. The total number of hydrophone less than 4 is not recommended due to a limited final precision, being able to localize an average of 60% of the total number of pings. Table VI presents the results from the 2 best variants (Partial4-HD and Partial 2-HD). The same table also presents the final comparison of using SF and not using SF, having an improvement of over 30% to the SSP close to the source and only 5% to the SSP close to the received.

Table VI .Percentage of pings detected with maximal error from the true position up to 1 km. Two SSP were used (close to the source and close to the receiver). The direction used in both cases was received to simulated.

SSP close to the source								
	Partial4-HD No SF		Partial4-HD SF disk 9-9		Partial2-HD No SF		Partial2-HD SF disk 9-9	
Array 64 Hydrophones (from hydrophone 1 to 64)	65%	Red.	99%	Red.	73%	Red.	100%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	65%	0.0%	98%	-1.0%	73%	0.0%	100%	0.0%
Array 16 Hydrophones (from hydrophone 1 to 64)	64%	-1.5%	95%	-4.0%	71%	-2.7%	99%	-1.0%
Array 8 Hydrophones (from hydrophone 1 to 64)	60%	-7.7%	92%	-7.1%	71%	-2.7%	100%	0.0%
Array 4 Hydrophones (from hydrophone 1 to 64)	61%	-6.2%	83%	-16.2%	71%	-2.7%	96%	-4.0%
Array 2 Hydrophones (from hydrophone 1 to 64)	53%	-18.5%	68%	-31.3%	63%	-13.7%	83%	-17.0%
SSP close to the receiver								
	Partial4-HD No SF		Partial4-HD SF wiener 11-11		Partial2-HD No SF		Partial2-HD SF wiener 11-11	
Array 64 Hydrophones (from hydrophone 1 to 64)	92%	Red.	97%	Red.	89%	Red.	92%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	92%	0.0%	94%	-3.3%	89%	0.0%	91%	-1.1%
Array 16 Hydrophones (from hydrophone 1 to 64)	93%	1.1%	95%	-2.2%	89%	0.0%	88%	-4.3%
Array 8 Hydrophones (from hydrophone 1 to 64)	85%	-6.9%	91%	-6.5%	88%	-1.1%	91%	-1.1%
Array 4 Hydrophones (from hydrophone 1 to 64)	82%	-10.3%	81%	-16.3%	84%	-5.6%	82%	-10.9%
Array 2 Hydrophones (from hydrophone 1 to 64)	66%	-27.6%	66%	-31.5%	60%	-32.6%	69%	-25.0%

1.1 Coherence between hydrophones

The last analysis on this chapter was to define the minimal spacing between hydrophones which results in a diversity gain by increasing the decoherence between sensors. 2 hydrophones were used with variations on the spacing between them, starting from spacing of 1 hydrophone, 3 hydrophones, 7 hydrophones, 15 hydrophones and 31 hydrophones.

Table VII .Percentage of pings detected with maximal error from the true position up to 1 km. the SSP close to the source and close to the receiver were used. The direction used was received to simulated. The depths were disregarded.

% detection in range with accepted error up to 1km (SSP close to the source) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
1 Hydrophone (Hydrophone 50)	No S. Filter	35%	26%	24%	21%	20%	25%	27%	20%
	SF-disk 9	62%	81%	39%	39%	48%	59%	67%	58%
Spacing of 1 hydrophone (Hydrophone 1 and 2)	No S. Filter	49%	52%	37%	14%	44%	51%	52%	48%
	SF-disk 9	74%	77%	24%	7%	43%	57%	63%	63%
Spacing of 3 hydrophones (Hydrophone 1 and 4)	No S. Filter	56%	52%	42%	13%	39%	44%	51%	54%
	SF-disk 9	78%	87%	29%	6%	46%	61%	77%	71%
Spacing of 7 hydrophones (Hydrophone 1 and 8)	No S. Filter	54%	57%	37%	25%	46%	52%	51%	49%
	SF-disk 9	73%	88%	33%	11%	49%	73%	82%	74%
Spacing of 15 hydrophones (Hydrophone 1 and 16)	No S. Filter	51%	54%	39%	22%	53%	53%	54%	58%
	SF-disk 9	79%	87%	38%	13%	54%	75%	82%	79%
Spacing of 31 hydrophones (Hydrophone 1 and 32)	No S. Filter	65%	58%	54%	28%	59%	60%	61%	67%
	SF-disk 9	82%	92%	51%	19%	65%	81%	89%	85%
% detection in range with accepted error up to 1km (SSP close to the receiver) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
1 Hydrophone (Hydrophone 50)	No S. Filter	52%	52%	38%	27%	55%	58%	59%	55%
	Wiener 11	40%	48%	48%	19%	55%	63%	54%	56%
Spacing of 1 hydrophone (Hydrophone 1 and 2)	No S. Filter	47%	53%	44%	26%	52%	60%	57%	58%
	Wiener 11	37%	48%	48%	29%	57%	62%	58%	62%
Spacing of 3 hydrophones (Hydrophone 1 and 4)	No S. Filter	37%	44%	53%	26%	59%	57%	49%	56%
	Wiener 11	32%	45%	53%	29%	62%	57%	51%	53%
Spacing of 7 hydrophones (Hydrophone 1 and 8)	No S. Filter	40%	60%	65%	27%	68%	64%	59%	66%
	Wiener 11	33%	58%	60%	36%	68%	66%	66%	63%
Spacing of 15 hydrophones (Hydrophone 1 and 16)	No S. Filter	38%	54%	58%	29%	73%	65%	61%	68%
	Wiener 11	35%	63%	67%	33%	75%	72%	63%	69%
Spacing of 31 hydrophones (Hydrophone 1 and 32)	No S. Filter	46%	64%	56%	28%	67%	73%	65%	66%
	SF-Wiener 11	37%	68%	63%	38%	75%	77%	71%	65%

As the spacing between the two hydrophone increases, the decoherence between the received signal also increases, which means that fadings are likely to happen in different time, thus the combination results in an improvement at the localization accuracy. For the table VIII the SSP adopted was the one close to the receiver. Overall the best cost-benefit was found by the spacing comprised by 15 hydrophones (array size of 2.4 m). Array with higher length would experience satisfactory decoherence between sensor, as shown at table VIII.

Table VIII .Percentage of pings detected with maximal error from the true position up to 1 km. The SSP close to the source was used. The direction used was received to simulated.

SSP close to the source								
	Partial4-HD No SF		Partial4-HD SF disk 9-9		Partial2-HD No SF		Partial2-HD SF disk 9-9	
1 Hydrophone (hydrophone 50)	20%	Gain	48%	Gain	25%	Gain	59%	Gain
Spacing of 1 hydrophone (hydrophones 1 and 2)	44%	120.0%	43%	-10.4%	51%	104.0%	57%	-3.4%
Spacing of 3 hydrophones (hydrophones 1 and 4)	39%	95.0%	46%	-4.2%	44%	76.0%	61%	3.4%
Spacing of 7 hydrophones (hydrophones 1 and 8)	46%	130.0%	49%	2.1%	52%	108.0%	73%	23.7%
Spacing of 15 hydrophones (hydrophones 1 and 16)	53%	165.0%	54%	12.5%	53%	112.0%	75%	27.1%
Spacing of 31 hydrophones (hydrophones 1 and 32)	59%	195.0%	65%	35.4%	60%	140.0%	81%	37.3%
SSP close to the receiver								
	Partial4-HD No SF		Partial4-HD SF wiener 11-11		Partial2-HD No SF		Partial2-HD SF wiener 11-11	
1 Hydrophone (hydrophone 50)	55%	Gain	55%	Gain	58%	Gain	63%	Gain
Spacing of 1 hydrophone (hydrophones 1 and 2)	52%	-5.5%	57%	3.6%	60%	3.4%	62%	-1.6%
Spacing of 3 hydrophones (hydrophones 1 and 4)	59%	7.3%	62%	12.7%	57%	-1.7%	57%	-9.5%
Spacing of 7 hydrophones (hydrophones 1 and 8)	68%	23.6%	68%	23.6%	64%	10.3%	66%	4.8%
Spacing of 15 hydrophones (hydrophones 1 and 16)	73%	32.7%	75%	36.4%	65%	12.1%	72%	14.3%
Spacing of 31 hydrophones (hydrophones 1 and 32)	67%	21.8%	75%	36.4%	73%	25.9%	77%	22.2%

5.8. Chapter Summary

The purpose of the at-sea Alma 2015 experiment was to study of the influence of fluctuations due to wavefront distortion and decoherence effect on the medium, using different temporal and spatial scales. In this work it was used to validate the proposed inversion technique using eight different HD variants with respect to its precision. The information of the time difference of arrival (TDOA) as well as the angle of arrival (AOA) were used to the comparison between measured and modelled data. The first analysis was performed using only one hydrophone from the total 64 hydrophone array showing poor localization performance.

This problem will be tackled by considering an array of hydrophone, where it is known that the interference patterns does not likely happen at the same time on different uncorrelated hydrophones. So, the next section divided the analysis of the full array in two methods: the first one described in this chapter was using the spatial diversity between sensors, and the next one using the beamforming, where the results will be presented on the next chapter. The next section on this chapter introduced the concept of spatial filtering and presented the improvement on the performance for localization. Two SSP were analysis on this chapter, the first measured close to the source and the second close to the receiver. The two remaining SSP, the SSP evaluated by the mean of two previous SSP and the SSP close to the source simulated by the X.Program, were presented at the appendix E and F. The last section of this chapter defined the minimal number of the hydrophones as well as the minimal spacing between sensors for this environment to achieve a minimal of 90% of detection in range. Localization was considered successful if the error was smaller than 1km (around 10% of the target range).

CHAPTER 6

Alma 2015 Experiment – Beamforming

Contents

6.1. Introduction	83
6.2. Beamforming.....	85
6.3. Results Adaptive synchronization	86
6.3.1 SSP close to the Source	91
6.3.2 SSP close to the Receiver	96
6.4. Minimal number of Hydrophones.....	101
6.5. Best Configuration.....	103
6.6. Cramer Rao bound	104
6.7. Array Section	109
6.8. Chapter Summary	112

6.1. Introduction

The second part of the Alma 2015 analysis presents the at-sea experimental results of the variants Hausdroff Distance (HD) using the Beamforming technique. The beamforming combines the energy of the received signal given its direction of arrival (DOA) while attenuate the energy for the others directions. The results were obtained using the first 95 transmitted pings (same transmitted pings used to the Spatial diversity), and the comparison of both techniques will be presented here. This chapter also provides the results of using a sector of the array with the size of 1/3 of the original array. By reducing the array size from 10m to 3m it is possible to operate in combat vessels including in an operational submarine.

The beamforming techniques present some advantages: it is likely more robust at low SNR, due to the combination of the signals from the total number of hydrophones and it reduces the problem generated by the temporal resolution on the peaks detection applied on the received signal due to its angular separation. If two eigen rays arriving at close time interval (chosen to be $4 \cdot 1/BT$) form different direction of arrival, the peak detection is able to identify only the highest intensity peak of the two direction by using the spatial diversity technique due to its temporal limitations, however by increasing the dimension (information

not only from the time but also from the angle) even if two eigen rays arrive at the same time, they can be separated considering the angular information by using the beamforming technique. The angular resolution depends on the total number of hydrophones.

On the Spatial diversity, each one of the 16 HD variants (8 variants for the forward direction and 8 variants for the backward) is going to be evaluated to each hydrophone and then the output is going to be combined (mean, median or max of all hydrophones) to a final result, as shown at Fig. 52 (top). The beamforming process differs from the spatial diversity by instead of evaluate the HD for each hydrophone and then combine to a final result, it first combines all the hydrophones which result in a gain (when the signals are coherent) at the direction of the arrival Eigen ray and then the HD is evaluated using the information of the TDOA and the DOA, as shown at Fig. 52 (bottom). A process called adaptive peak detection was introduced and it will be discussed in this chapter. By reducing the number of HD operations, from the total number of hydrophones isolated 64 to only one which is a vector with the combination of all hydrophones in 2 dimensions: information of time (TDOA) and angle (DOA), the beamforming presents a reduced computational time compared with the spatial diversity. 14 variants of Hausdorff Distance were used to the beamforming. The ProbHD was eliminated because the reduced numbers of elements in a final vector (64 times less due to the beamforming). The next step to both methods was to use the spatial filtering, consisting of a total of 46 different filtering. At the end by search for the minimal value of error, it is possible to estimate the location in range and in depth of the target.

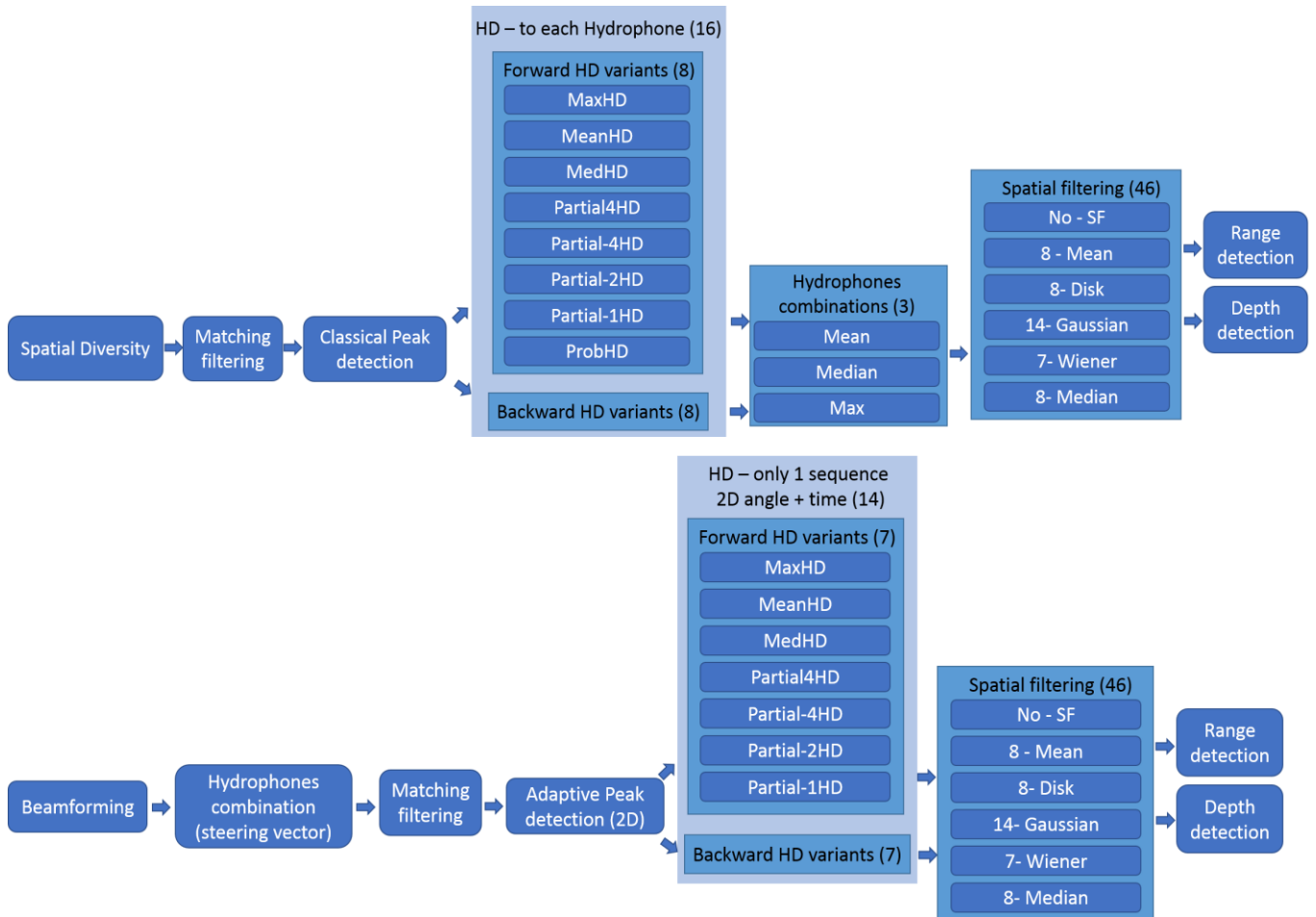


Fig. 52. Flowchart of both Methods.

6.2. Beamforming

Three SSP described on the last chapter are now compared using the information of the Direction of arrival (DOA) and Time difference of arrival (TDOA) at the true target location, shown at Fig. 53. The SSP close to the receiver presents the higher variations on the angle information.

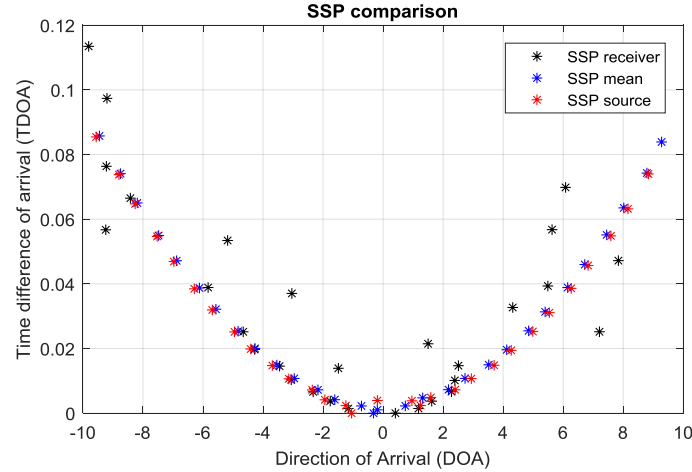


Fig. 53. SSP comparison for true position of the source (9km in range and 56m in depth).

The process of localizing using beamforming is defined following three steps:

- 1) Sum of the received signal at all hydrophones, linear delayed in time based on the information from the direction of arrival (DOA). This process is performed in frequency domain through the steering vector. For each look direction, it performed the inner product of the steering phase shift vector with the data vector. This inner product is the spatial equivalent of a matched filter.
- 2) Matched filtering the output of the beamforming, for each variation in angle, with the transmitted signal and apply the Fourier transform to time domain. Searching for the peaks performed in 2D, angle and time, characterizing the impulse response as shown at Fig. 54. The symbol “x” black color corresponding to the modeled TDOA and the red circle represent the measured TDOA. The Modeled TDOA presented at Fig. 54, was evaluated on the true source position, 9 km in range (left - better resemblance between two data set) and on 6km range (right – wider hyperbole due to a high value of angles to a close distance). Both cases with the center of the array at 56 m in depth.

3) The Hausdorff Distance (HD) variants are applied using the combination of both, time and angle information. The comparison between the two data set, TDOA measured and TDOA simulated, was performed by the square root of the time difference squared multiply for a weight of 10^3 plus the angle difference squared. This weight was applied on the time information to compensate the order of magnitude between the time and angle with a relation ratio 10^3 . The two marginal direction, forward HD $h(R_t, S_t)$ and backward HD $h(S_t, R_t)$, were analyzed, and again the results from each marginal direction are not symmetric and are based on the number of the TDOA, however because it was evaluated based on the combination of the total number of hydrophones, the eigen rays are more likely of being detected when compared with the results from each isolated hydrophone.

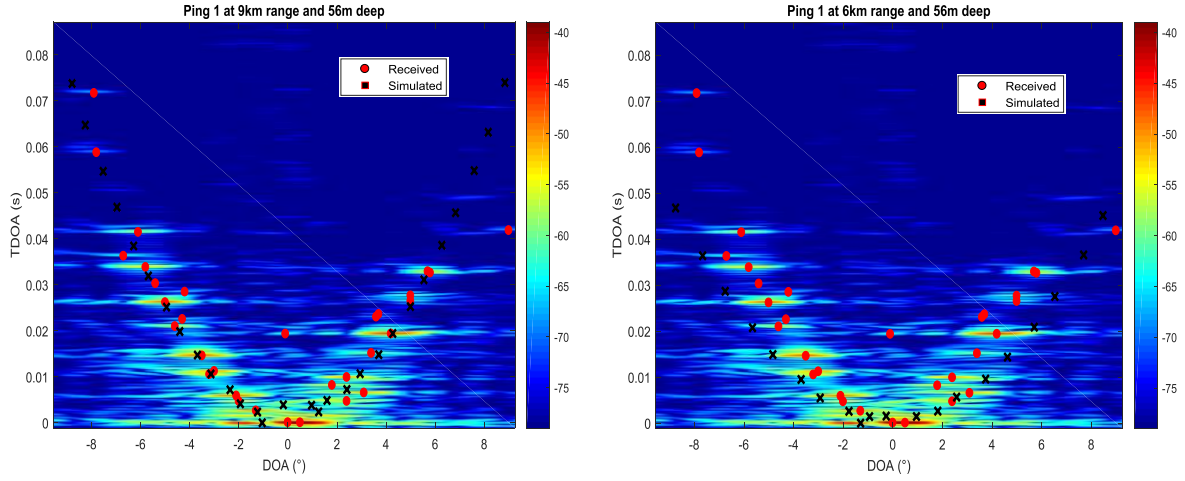


Fig. 54. TDOA peak comparison. Red (measured) and Black (modeled) at 9 km (left) and 6 km (right).

6.3. Results Adaptive synchronization

The peak detection from the beamforming was first implemented searching for the high intensity value after the matched filtering, process similar to the one applied on the spatial diversity. The results are presented on the table IX named as max peak detection evaluated to the SSP close to the source. As explained on the last chapter this detection is valid to the spatial diversity because it is likely that the fading happens in different time of arrival considering a long array (decoherence between hydrophones), thus at least one hydrophone can detect the correct value of the first arrival used as reference to all the remaining TDOA sequences of the total number of hydrophones. Different from the spatial diversity the beamforming technique does not analyze each hydrophone isolated, so even if the correct value to the first arrival used to synchronize the TDOA sequence can be detected to a certain hydrophone, the combination with the reimagining hydrophone may reduce the intensity level to the correct first time of arrival while amplify a wrong position, which will be detected and used as a reference introducing a mismatch at the ambiguity surface. To solve this problem one possible solution would be applying a time shift vector to each interaction of the HD, selecting the minimal index value of all interactions, which means the most resemblance between both sequences. However, this process would request a higher processing time as the number of elements to the time shift vector increases. The second disadvantage to this process is that it would be applied to all pings, including the ones that had correctly detected the first arrival to the reference. For example, a time shift vector with a step of 1 milliseconds with 100 elements, accepting a total variation in time of 0.1s. This step would require an increment of 100 times to the processing time. A second solution and the one used in this work was the development of adaptive peak detection. The results are presented on table IX named as adaptive detection both to the range and to the depths. Different from the previous case, this process is only applied in case of a second peak detection or more, limited to six detection, over a threshold defined as 15dB under the value of maximal detected peak and before its arrival in time.

On the ping number 5 shown at Fig. 55, a second Peak was detected before the arrival of the maximal detected peak (black circle). The position in time of the second maximal peak is going to be used as reference resulting on the ambiguity function shown at Fig. 56. If more peaks were detected under the defined threshold, the HD would be performed to this new position until reaches a limit defined as 6 interactions. The most similar are both sequences, Modeled and Measured, from each other the less will be the minimal value at the ambiguity surface for each HD variant, registered to each interaction. A final search for the minimal value of the total number of interaction is performed, having a high probability of finding the correct value to the first reference in time. On Fig. 56 the value of the ambiguity surface was inverted to a better visualization ($1/\text{HD}$), thus the best case was found using the second maximal detected peak value (2° max) as reference, which gives a high value of its peak index on the Fig. 56. By applying the Adaptive detection on the ping number 5 correcting the value of the peak used as reference it was possible to detect the target under the defined 1km error in range and 10 m in depths Fig. 56 (right). The Adaptive detection in the worst scenario increases no more than the total amount of interactions, which in this case is 6 times the processing time. This process is more optimized than the previous one (100 times).

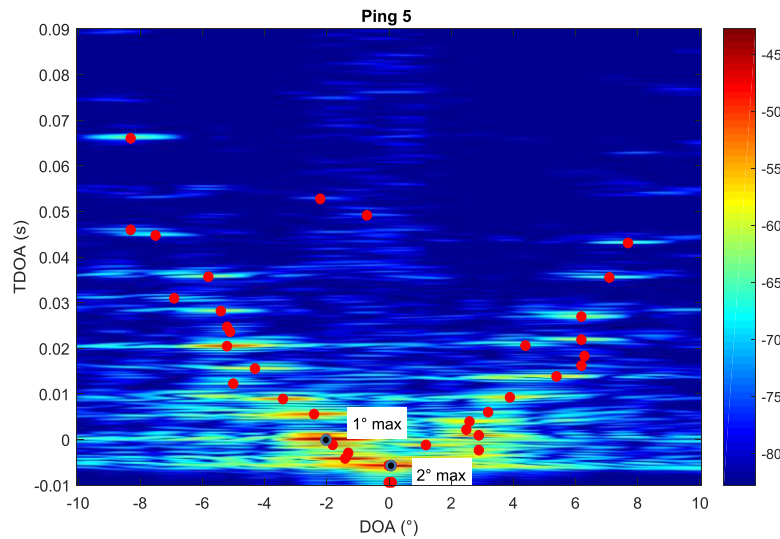


Fig. 55. Adaptive peak detection.

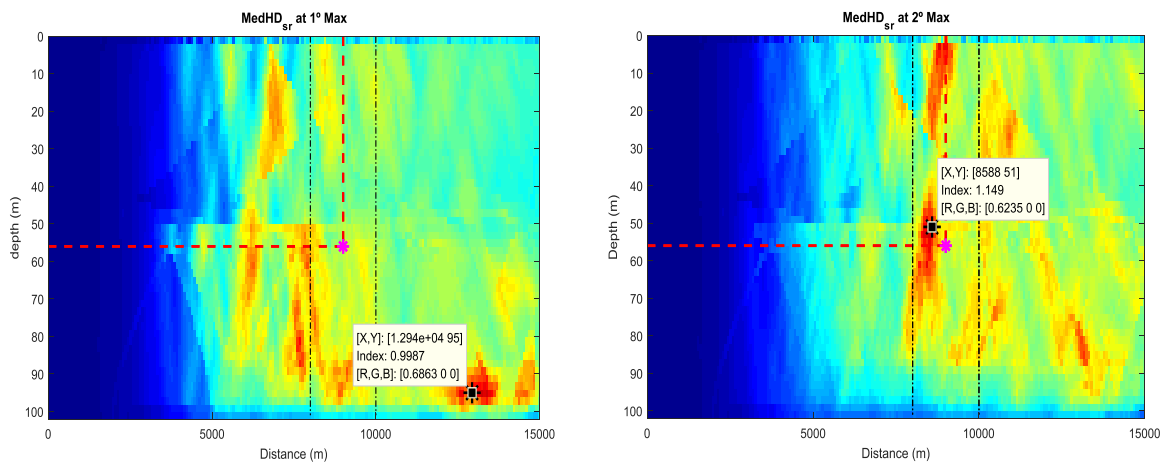


Fig. 56. Ambiguity function to the MedHD variant applied on the TDOA sequence using the wrong position as reference in time (left – 1 max) and using the correct position as reference (right – 2 max).

The first analysis was performed to measure the improvement from using the Adaptive peak detection. Using the SSP close to the source, the HD variants were performed to find the target location either in range and in depths, first considering only the maximum value as reference and second using the Adaptive peak detection. Seven variants of HD were used to this analysis, same variants used to the spatial diversity with an exception of the ProbHD (see chapter 3).

Table IX .Percentage of pings detected with maximal error from the true position up to 1 km and 10 m in depth. The SSP close to the source was used. Both directions (forward and backward) are presented.

Synchronization		MaxHD	MeanHD	MedHD	Partial4HD	Partial4-HD	Partial2-HD	Partial1-HD
HD direction received to simulated (Forward HD)								
range	Max Peak detection	14%	55%	54%	25%	57%	55%	54%
	Adaptive detection	13%	72%	79%	28%	67%	67%	66%
depth	Max Peak detection	18%	49%	48%	24%	46%	51%	48%
	Adaptive detection	18%	59%	75%	37%	62%	63%	63%
HD direction simulated to received (Backward HD)								
range	Max Peak detection	9%	8%	60%	24%	45%	31%	20%
	Adaptive detection	20%	38%	91%	23%	69%	48%	41%
depth	Max Peak detection	29%	28%	56%	28%	68%	57%	40%
	Adaptive detection	47%	58%	78%	44%	82%	68%	58%

Fig. 57 and Fig. 58, shows the histogram comparison of both peak detection. The Adaptive peak detection has shown a significant increase in performance. The MedHD variant was used to show the histogram. Fig. 57 presents the forwards HD and Fig. 58 shows the backwards HD. Plot on the left shows the detection in range and plot on the right show the detection on depths. The red color represents the peak detection using the Max value and blue color represents the peak detection based on the proposed adaptive detection. The mean and the standard deviation of the results in range and in depths were also evaluated by the function `evfit` in MATLAB. The blue and red dashed lines represent the extreme value probability density function evaluated by the function `evpdf` in MATLAB, which used the value of μ (green dotted line) and σ from the previous MATLAB function. The red line represents the true source location both in range (9km) and in depth (56m).

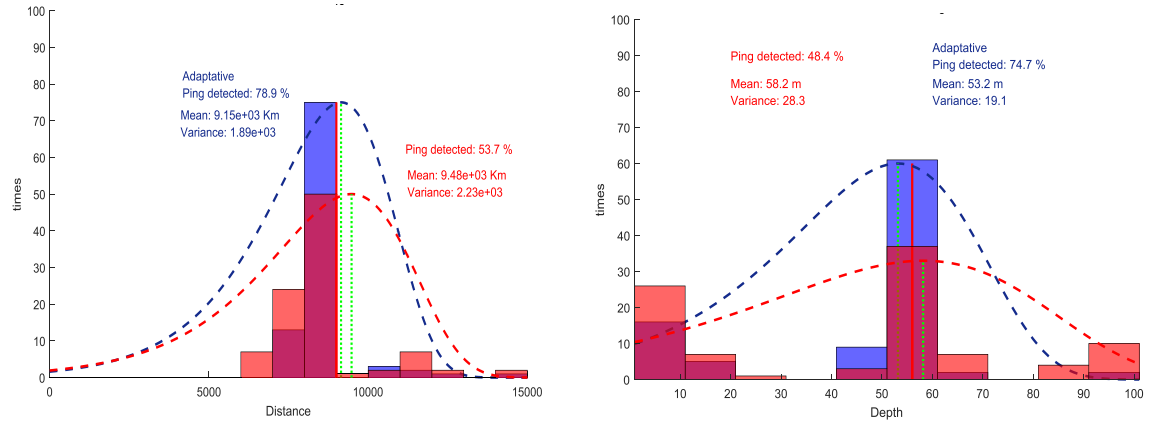


Fig. 57. Histogram of the MedHD from the direction of received to simulated, in range (left) and in depths (right).

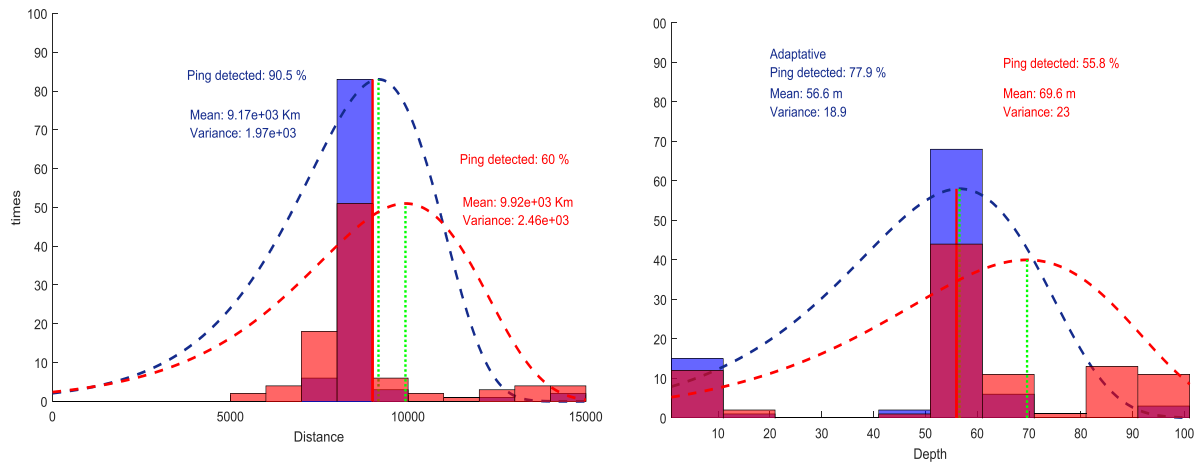


Fig. 58. Histogram of the MedHD from the direction of simulated to received, in range (left) and in depths (right).

Overall with the adaptive peak detection the correct target detection, considering the best overall variants (MedHD), was increased in range up to 35 % to the forward HD and 50% to the backward HD and the detection in depths was increased to 55% to the forward HD and 40% to the backward HD. The second conclusion from the beamforming results compared with the results from spatial diversity is the higher precision on finding the true depths location, while reaching almost similar results on range accuracy.

The total 95 pings were defined in 2 groups: the first one being the first 50 pings and the second the 45 remaining pings. The second group experiences the worst results especially to the range detection as shown at Fig. 59 and Fig. 60 due to a loss of coherence between hydrophones. A study to better understand the reason for this decoherence are still in progress, however it is expected that the surface spreading and variations of the roughness of the sea surface due to increasing of the wind speed may be responsible. This decoherence is responsible for variations of the peak intensity on the first arrival leading to a wrong reference position. The adaptive peak detection reduces the influence of the decoherence of the hydrophones and it was used to all the subsequent results. Red color represents the detection based on the max peak; blue color represents the detection based on the proposed adaptive peak detection. On the left, it was performed to the location in range and on the right to the location in depths.

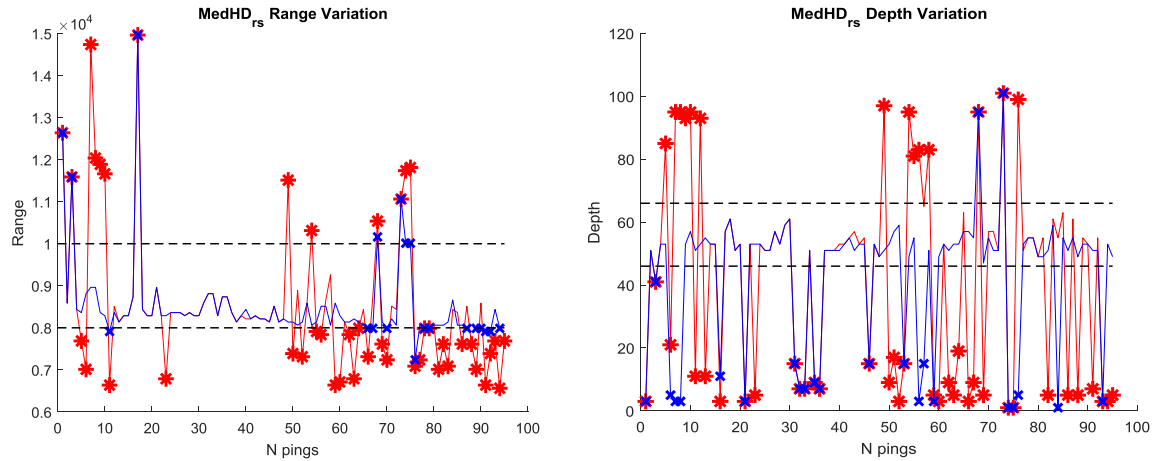


Fig. 59. Variation of the detected range (left) and detected depth (right) from the direction of received to simulated: Max peak detection (red line), Adaptive peak detection (blue line).

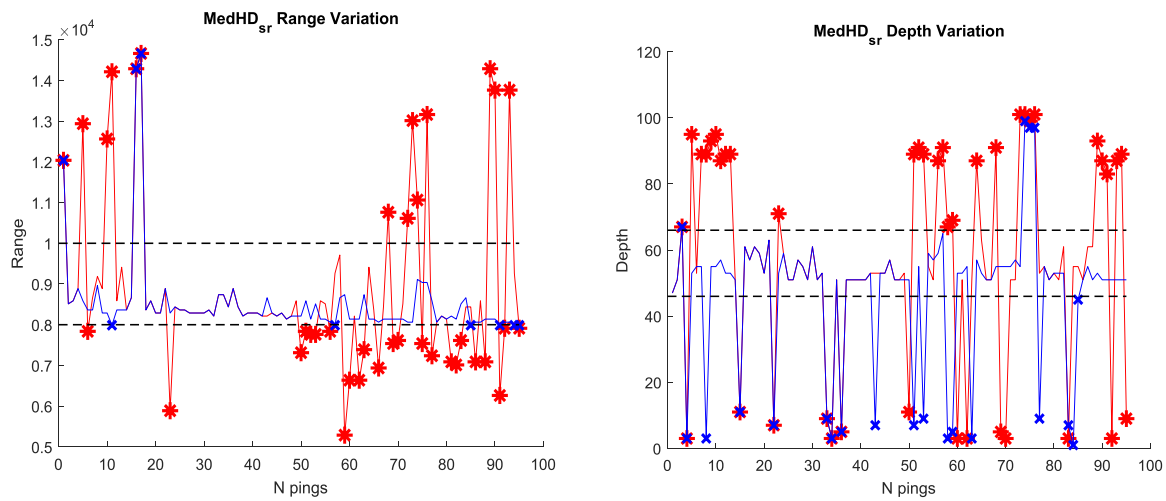


Fig. 60. Variation of the detected range (left) and detected depth (right) from the direction of simulated to received: Max peak detection (red line), Adaptive peak detection (blue line).

Since that the spatial diversity technique consider the information from each isolated hydrophone, it is far more robust to those decoherence problem. The second conclusion is that the beamforming has a better results from using the backward HD (simulated to the receiver). The reason for the HD performed badly using the direction of simulated to received on the Spatial diversity is that the peak detection on the measured TDOA is limited by the temporal resolution, so close arrival in time will one identify one path. The Simulated TDOA has no limitation leading with more information from different Eigen rays generating high value of ambiguity. The beamforming can separate close time of arrivals by the angle of arrival thus having a better performance on the final localization. The second problem from using the direction of simulated to the received in evaluating the HD is presented when the simulation was performed using the SSP close to the receiver. Each position of the rasterized grid of simulation with variation in range and depth will have its own TDOA simulated which will be compared with the TDOA measured. The simulation using the SSP close to the receiver presents at some position a reduced number of elements in the sequence of TDOA simulated. The simulation was performed defining a maximal number of Eigen rays of 30 paths, however due to the wave propagation for this particular SSP, the position at 15 km range and 100m

deep was able to detect only 2 paths. Once used as reference to the HD, it will only consider 2 elements thus resulting in high value on the ambiguity surface leading to a wrong location of the target. One possible solution is to eliminate the position on the rasterized grid of simulations with less than a minimal accepted number of elements. The second solution is to use the information of its neighborhood through the spatial filtering, valid when the size of the window used to filtering the output of HD is higher than the number of points on the rasterized grid of simulation containing only few elements.

As for the spatial diversity, the beamforming was performed with different number of hydrophones in order to identify the accepted minimal number of hydrophones. The use of spatial filtering was also evaluated using the 5 different kernels with variation in window size similar as used on the spatial diversity. However, in the case of beamforming some configurations presents a worst result when using spatial filtering, which is different from the spatial diversity where all the configurations were benefited with the spatial filtering.

6.3.1 SSP close to the Source

The first SSP used was measured close to the source and are presented at table X to the range and table XI to the depth detection. The first section of the table shows the result in range from using the direction of the received TDOA sequence to the simulated TDOA sequence (Forward HD) and the second section the reverse direction (Backward HD), evaluated to the main seven HD variants. First line on each configuration shows the result from using the adaptive peak detection with no spatial filtering, named as “No S.Filter”, follow by the use of spatial filtering, showing the 2 best results, which are the SF with kernel mean with window size of 9-by-9 and the kernel disk with window size of 9-by-9, depending on the SPP.

Table X .Percentage of pings detected with maximal error from the true position up to 1 km in **range**. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

And Table XI .Percentage of pings detected with maximal error from the true position up to 10 m in **depth**. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

% detection in range with accepted error up to 1km (SSP close to the source) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	13%	72%	79%	28%	67%	67%	66%
	SF-Mean 9	38%	66%	84%	36%	67%	59%	58%
	SF-Disk 9	42%	55%	80%	38%	56%	54%	52%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	14%	68%	74%	31%	65%	67%	66%
	SF-Mean 9	42%	65%	82%	38%	68%	63%	59%
	SF-Disk 9	44%	53%	77%	37%	54%	55%	53%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	11%	66%	78%	34%	65%	66%	66%
	SF-Mean 9	42%	61%	83%	36%	66%	64%	62%
	SF-Disk 9	45%	47%	75%	42%	53%	48%	49%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	22%	63%	71%	40%	66%	62%	63%
	SF-Mean 9	59%	68%	77%	43%	66%	63%	63%
	SF-Disk 9	59%	60%	68%	48%	52%	49%	51%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	6%	26%	54%	41%	40%	29%	29%
	SF-Mean 9	38%	25%	49%	43%	32%	31%	29%
	SF-Disk 9	49%	28%	27%	47%	22%	22%	25%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	7%	8%	22%	32%	22%	17%	13%
	SF-Mean 9	53%	24%	20%	33%	21%	23%	27%
	SF-Disk 9	64%	28%	12%	34%	21%	32%	36%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	20%	38%	91%	23%	69%	48%	41%
	SF-Mean 9	0%	13%	91%	32%	52%	29%	23%
	SF-Disk 9	0%	2%	82%	38%	42%	21%	8%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	21%	40%	92%	25%	68%	44%	39%
	SF-Mean 9	0%	16%	92%	38%	53%	31%	21%
	SF-Disk 9	0%	2%	80%	38%	44%	21%	11%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	19%	41%	85%	33%	65%	43%	37%
	SF-Mean 9	0%	11%	85%	37%	44%	27%	19%
	SF-Disk 9	0%	1%	75%	42%	40%	26%	9%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	6%	38%	89%	38%	73%	56%	39%
	SF-Mean 9	0%	8%	86%	41%	52%	22%	19%
	SF-Disk 9	0%	1%	64%	48%	33%	16%	7%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	2%	24%	77%	39%	44%	36%	26%
	SF-Mean 9	4%	12%	61%	44%	29%	17%	15%
	SF-Disk 9	1%	5%	42%	48%	16%	8%	7%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	9%	20%	33%	32%	34%	27%	25%
	SF-Mean 9	9%	8%	22%	29%	16%	15%	12%
	SF-Disk 9	5%	9%	15%	28%	14%	12%	8%

% detection in depth with accepted error up to 10m (SSP close to the source) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	18%	59%	75%	37%	62%	63%	63%
	SF-Mean 9	13%	41%	82%	16%	57%	53%	45%
	SF-Disk 9	8%	40%	66%	18%	45%	43%	42%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	19%	60%	78%	35%	65%	62%	58%
	SF-Mean 9	15%	44%	79%	20%	56%	51%	46%
	SF-Disk 9	9%	40%	65%	19%	45%	43%	43%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	16%	59%	81%	38%	61%	57%	57%
	SF-Mean 9	18%	41%	89%	19%	60%	55%	48%
	SF-Disk 9	13%	41%	68%	24%	46%	43%	40%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	4%	46%	68%	33%	57%	53%	52%
	SF-Mean 9	2%	39%	80%	14%	53%	46%	42%
	SF-Disk 9	1%	36%	62%	17%	46%	40%	39%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	4%	13%	32%	19%	19%	15%	14%
	SF-Mean 9	0%	8%	36%	11%	17%	15%	12%
	SF-Disk 9	0%	4%	23%	12%	12%	6%	6%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	1%	8%	24%	4%	3%	1%
	SF-Mean 9	0%	2%	3%	16%	5%	4%	4%
	SF-Disk 9	0%	1%	2%	12%	2%	2%	1%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	47%	58%	78%	44%	82%	68%	58%
	SF-Mean 9	7%	32%	91%	17%	72%	46%	40%
	SF-Disk 9	2%	12%	85%	22%	51%	25%	17%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	51%	61%	85%	42%	82%	64%	53%
	SF-Mean 9	8%	32%	89%	19%	66%	44%	33%
	SF-Disk 9	1%	8%	87%	23%	47%	22%	14%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	49%	65%	83%	40%	83%	62%	54%
	SF-Mean 9	9%	29%	89%	20%	66%	38%	35%
	SF-Disk 9	3%	8%	83%	24%	41%	25%	16%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	33%	58%	81%	37%	89%	74%	58%
	SF-Mean 9	18%	29%	88%	17%	69%	45%	38%
	SF-Disk 9	11%	11%	77%	19%	42%	28%	18%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	43%	58%	64%	18%	67%	58%	58%
	SF-Mean 9	31%	40%	61%	15%	45%	39%	42%
	SF-Disk 9	15%	19%	43%	15%	31%	20%	18%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	26%	55%	44%	29%	55%	54%	55%
	SF-Mean 9	34%	44%	45%	19%	43%	40%	45%
	SF-Disk 9	22%	35%	40%	18%	35%	34%	32%

Since that the combination of the hydrophones were performed before the HD given only one final measured vector with the information in time and angle, it was expected that the spatial filtering applied at the output of the HD variants would not give a big improvement at the localization. This result is different from the spatial diversity, and the reason is due to the spatial proximity property of the HD on each isolated hydrophone, allowing a small fluctuation on the target location to its neighborhood, given some small variations of the input TDOAs sequences. The SF is able to measure these small variations, reducing the ambiguity function, thus improving the accuracy up to 50% of the total amount of transmitted pings for the same SSP. On the beamforming, most of the corrections for the range detection occur on pings detected on the upper limit of 1km error, allowing to be detected on the limit of 1km, with only one considerable case shown as Fig. 61 for the ping number 3. The only benefit of using the SF, applied on the this SSP, happens on depth detection as shown on the ellipsoid of Fig. 62, where pings detected with a wrong value of depths could be corrected by the SF. Overall, the results from using the spatial filtering are better in depths detection with an improvement up to an average of 10% considering both HD directions, while for the range detection only 2.5% on average.

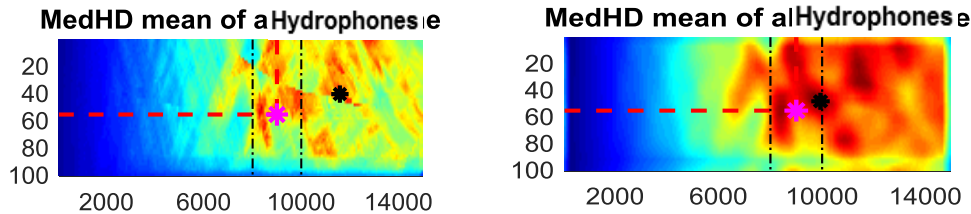


Fig. 61. Output of the MedHD from the direction of received to simulated without SF (left) and with SF mean 9-by-9 (right).

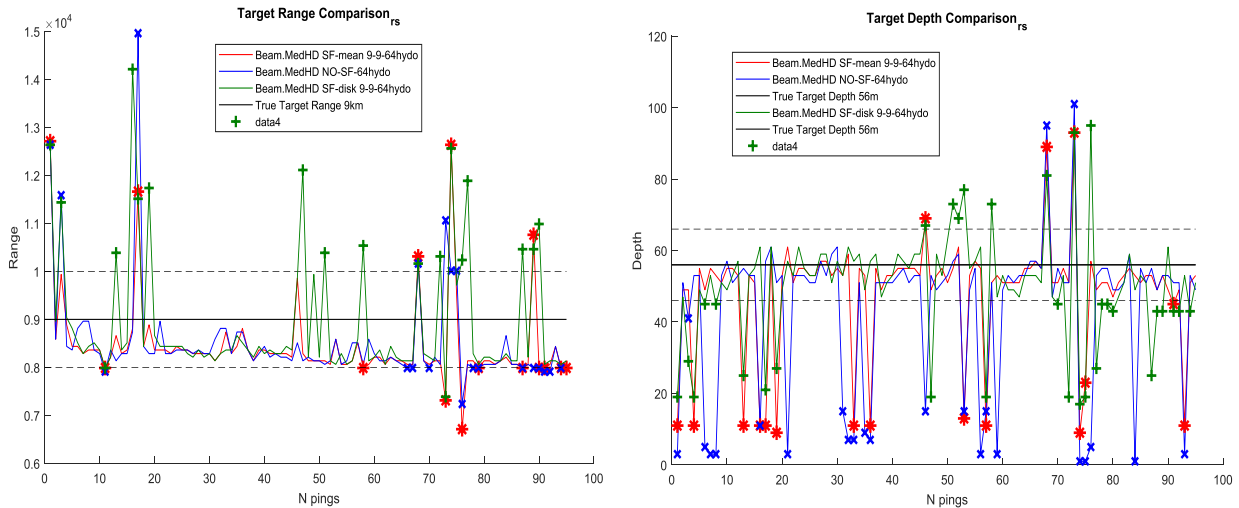


Fig. 62. Variation of the detected range (left) and detected depth (right) from the direction of received to simulated: with SF mean 9-by-9 (red line), without SF (blue line).

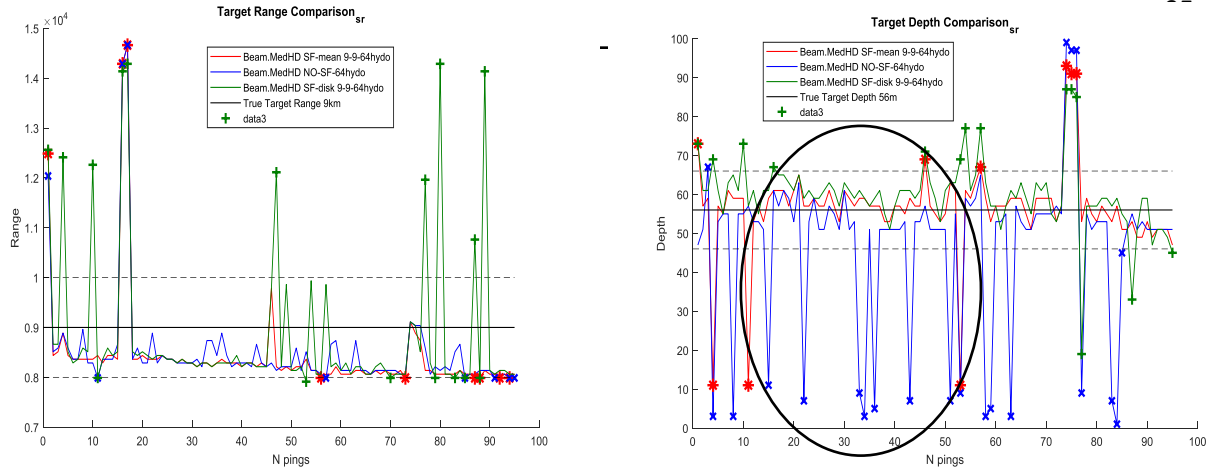


Fig. 63. Variation of the detected range (left) and detected depth (right) from the direction of simulated to received: with SF mean 9-by-9 (red line), without SF (blue line).

Fig. 64 presents the histogram to the best result from using the spatial diversity (red color) evaluated by the Partial-2HD with a spatial filtering disk 9-by-9, compared with the best result from using the Beamforming (blue color) evaluated by the MedHD with a spatial filtering mean 9-by-9. On the left performed for the range detection and on the right performed for the depth detection. Fig. 65 shows the variation of the detected range (left) and variation of the detected depths (right), compared with the true target location. Red line using the spatial diversity and blue line using the beamforming. The Spatial filtering is more accurate for detecting the correct target range, while the beamforming performs better to the depth target detection.

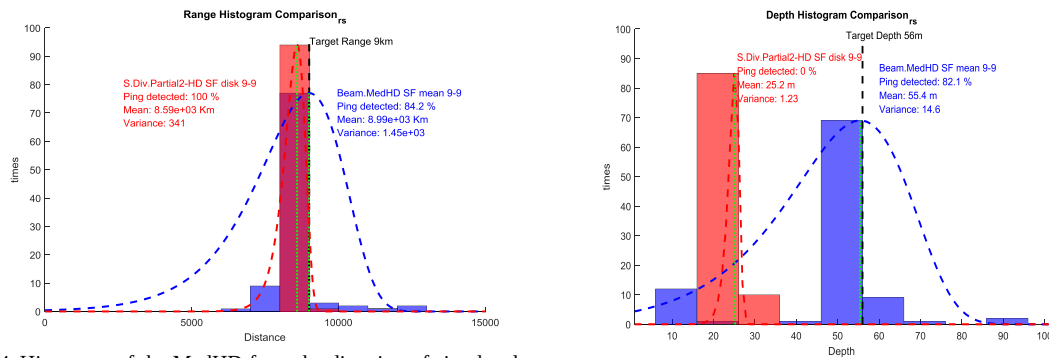


Fig. 64. Histogram of the MedHD from the direction of simulated to received, in range (left) and in depths (right).

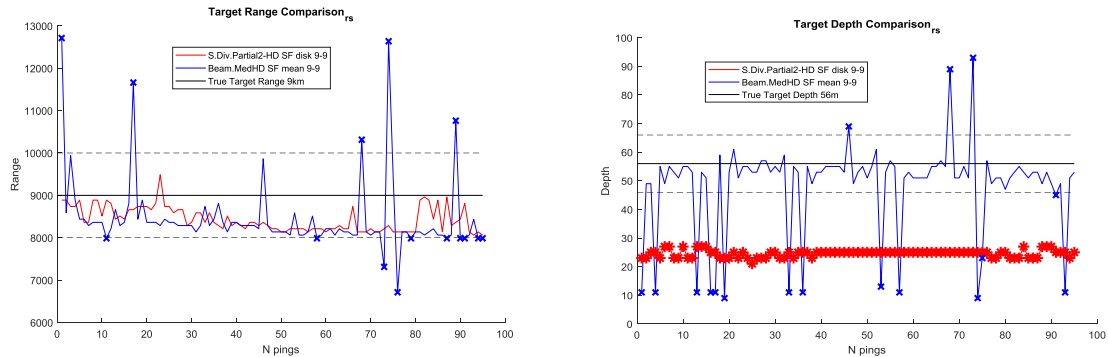


Fig. 65. Variation of the detected range (left) and detected depth (right) from the direction of received to simulated: best configuration to the Spatial diversity with SF disk 9-by-9 (red line), best configuration to the beamforming with SF mean 9-by-9 (blue line).

When applied on the HD backward direction, the results are better using the beamforming (blue color) either to range and depth detection as shown at Fig. 66 and Fig. 67, both using the MedHD with SF mean 9-by-9, compared with the spatial filtering (red color) using the Partial2-HD with SF disk 9-by-9.

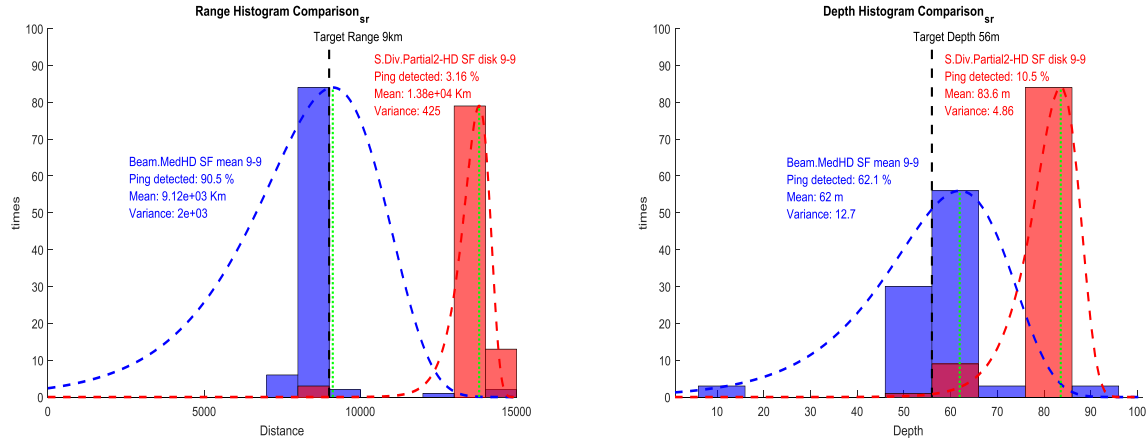


Fig. 66. Histogram of the MedHD from the direction of simulated to received, in range (left) and in depths (right).

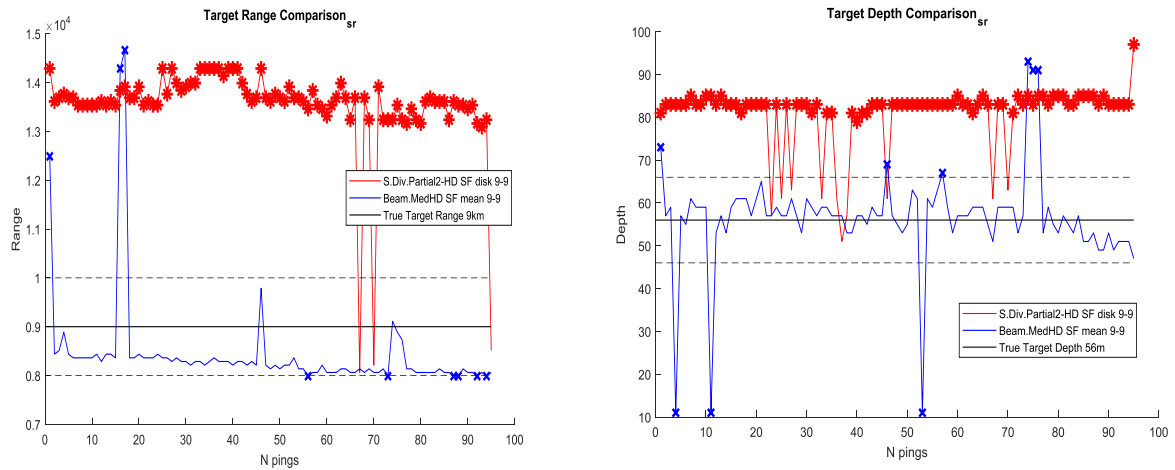


Fig. 67. Variation of the detected range (left) and detected depth (right) from the direction of simulated to received: best configuration to the Spatial diversity with SF disk 9-by-9 (red line), best configuration to the beamforming with SF mean 9-by-9 (blue line).

6.3.2 SSP close to the Receiver

Tables XII and XII show the result for the range detection from using the SSP close to the receiver for range detection and for depth detection respectively. Same configuration was used considering the same HD variants and same TDOA received. The only difference is the TDOA modelled used for the HD comparison. First section used for the Forward HD direction and the second section used for the Backward HD direction.

Table XII .Percentage of pings detected with maximal error from the true position up to 1 km in **range**. The **SSP used was measured close to the receiver** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

% detection in range with accepted error up to 1km (SSP close to the receiver) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	56%	91%	91%	43%	87%	87%	86%
	SF-Mean 9	55%	86%	94%	43%	82%	84%	82%
	SF-Disk 9	46%	77%	95%	49%	76%	74%	72%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	51%	93%	92%	43%	85%	85%	86%
	SF-Mean 9	56%	86%	94%	43%	83%	80%	79%
	SF-Disk 9	55%	78%	89%	51%	77%	77%	76%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	53%	88%	95%	44%	86%	87%	91%
	SF-Mean 9	65%	88%	95%	43%	79%	81%	81%
	SF-Disk 9	54%	77%	89%	46%	77%	77%	76%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	43%	85%	87%	51%	89%	87%	86%
	SF-Mean 9	46%	84%	91%	47%	86%	85%	85%
	SF-Disk 9	38%	78%	88%	51%	81%	80%	76%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	35%	72%	77%	62%	81%	81%	81%
	SF-Mean 9	42%	55%	71%	57%	67%	59%	59%
	SF-Disk 9	40%	49%	62%	65%	57%	46%	44%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	43%	41%	36%	37%	45%	44%	43%
	SF-Mean 9	35%	32%	27%	34%	26%	28%	27%
	SF-Disk 9	24%	19%	27%	36%	18%	17%	18%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	61%	36%	1%	2%	3%
	SF-Mean 9	0%	13%	87%	42%	37%	51%	32%
	SF-Disk 9	3%	7%	96%	45%	65%	26%	7%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	59%	45%	0%	2%	6%
	SF-Mean 9	0%	14%	89%	41%	29%	52%	38%
	SF-Disk 9	3%	5%	95%	45%	65%	25%	9%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	57%	42%	0%	3%	6%
	SF-Mean 9	0%	13%	87%	38%	32%	45%	34%
	SF-Disk 9	3%	7%	91%	42%	60%	27%	7%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	8%	67%	48%	1%	9%	12%
	SF-Mean 9	1%	17%	95%	46%	54%	58%	42%
	SF-Disk 9	3%	5%	88%	48%	63%	24%	8%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	3%	33%	59%	0%	1%	1%
	SF-Mean 9	6%	13%	55%	48%	29%	35%	15%
	SF-Disk 9	5%	5%	61%	60%	43%	17%	8%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	2%	5%	35%	0%	0%	2%
	SF-Mean 9	6%	4%	17%	29%	7%	7%	4%
	SF-Disk 9	3%	1%	18%	31%	16%	3%	0%

And Table XI .Percentage of pings detected with maximal error from the true position up to 10 m in **depth**. The **SSP used was measured close to the receiver** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

% detection in depth with accepted error up to 10m (SSP close to the receiver)								
HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	37%	80%	75%	44%	73%	75%	76%
	SF-Mean 9	49%	85%	86%	41%	81%	85%	82%
	SF-Disk 9	55%	85%	72%	31%	78%	78%	78%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	37%	77%	78%	40%	77%	77%	76%
	SF-Mean 9	51%	85%	89%	45%	84%	82%	82%
	SF-Disk 9	55%	86%	72%	33%	81%	85%	85%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	33%	82%	83%	39%	76%	76%	77%
	SF-Mean 9	56%	88%	89%	47%	86%	86%	86%
	SF-Disk 9	63%	84%	76%	36%	83%	84%	85%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	14%	71%	66%	43%	68%	72%	68%
	SF-Mean 9	33%	74%	77%	47%	80%	79%	78%
	SF-Disk 9	42%	78%	61%	35%	77%	80%	78%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	14%	42%	43%	44%	46%	44%	46%
	SF-Mean 9	27%	42%	54%	53%	63%	55%	51%
	SF-Disk 9	24%	44%	44%	39%	58%	51%	46%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	12%	18%	21%	36%	22%	19%	18%
	SF-Mean 9	14%	29%	29%	52%	36%	35%	29%
	SF-Disk 9	28%	41%	33%	44%	41%	42%	40%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	49%	38%	1%	2%	3%
	SF-Mean 9	0%	7%	83%	44%	75%	71%	44%
	SF-Disk 9	0%	0%	67%	33%	53%	25%	2%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	46%	41%	0%	2%	4%
	SF-Mean 9	1%	8%	82%	46%	68%	65%	42%
	SF-Disk 9	1%	0%	65%	34%	51%	24%	3%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	0%	44%	39%	0%	2%	4%
	SF-Mean 9	0%	4%	82%	52%	67%	62%	44%
	SF-Disk 9	1%	0%	63%	37%	49%	24%	2%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	5%	53%	45%	1%	9%	12%
	SF-Mean 9	0%	7%	80%	44%	84%	67%	39%
	SF-Disk 9	0%	0%	61%	37%	49%	21%	0%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	4%	29%	47%	1%	2%	2%
	SF-Mean 9	1%	2%	64%	49%	55%	33%	13%
	SF-Disk 9	0%	0%	49%	35%	25%	9%	2%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	1%	4%	37%	0%	0%	2%
	SF-Mean 9	1%	0%	22%	42%	19%	9%	6%
	SF-Disk 9	0%	2%	21%	35%	15%	5%	3%

Different from the results using the SSP close to the source, in this case (SSP close to the receiver) the use of spatial filtering mean 9-by-9 presents a good improvement either in range and depth detection, showing by the black ellipsoid on Fig. 68 and Fig. 69. Overall, the results from using the spatial filtering are still better in depths detection with an improvement up to an average of 27% considering both HD directions, while for the range detection only 17% on average.

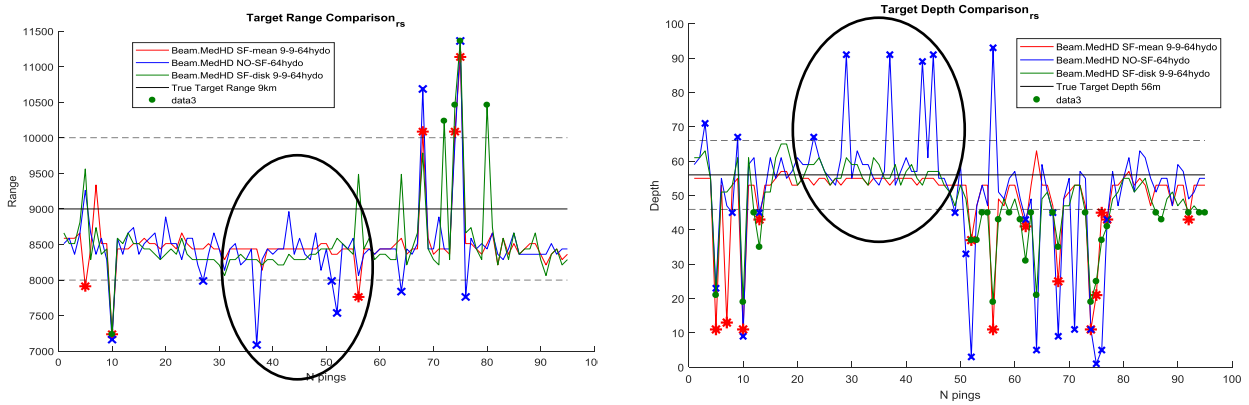


Fig. 68. Variation of the detected range (left) and detected depth (right) from the direction of received to simulated: with SF mean 9-by-9 (red line), without SF (blue line).

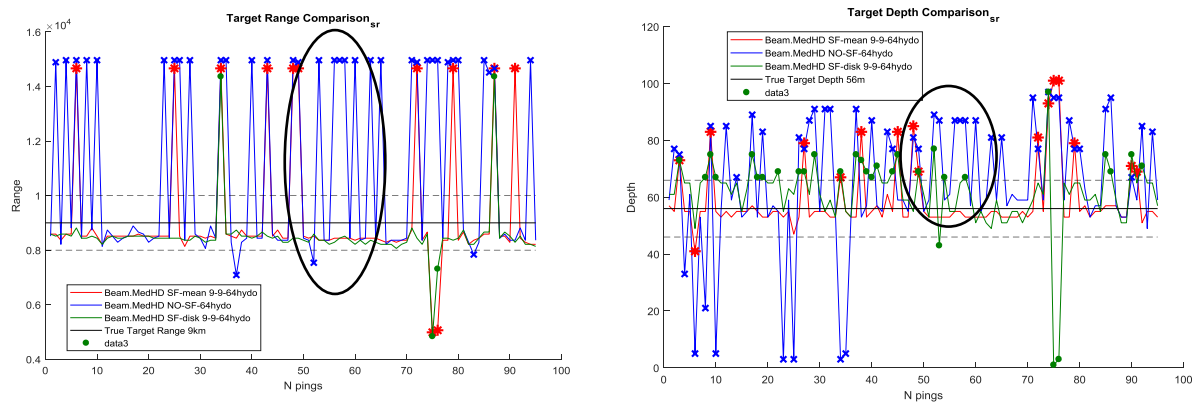


Fig. 69. Variation of the detected range (left) and detected depth (right) from the direction of simulated to received: with SF mean 9-by-9 (red line), without SF (blue line).

Fig. 70 presents the histogram to the best result from using the spatial diversity (red color) evaluated by the Partial-4HD with a spatial filtering wiener 9-by-9, compared with the best result from using the Beamforming (blue color) evaluated by the MedHD with a spatial filtering mean 9-by-9. On the left performed for the range detection and on the right performed for the depth detection. Fig. 71 shows the variation of the detected range (left) and variation of the detected depths (right), compared with the true target location. Red line using the spatial diversity and blue line using the beamforming. Once again, the Spatial filtering is more accurate for detecting the correct target range, while the beamforming performs better to the depth target detection. When applied on the backward HD, the results are better using the beamforming either to range and depth detection as shown at 0 and Fig. 73.

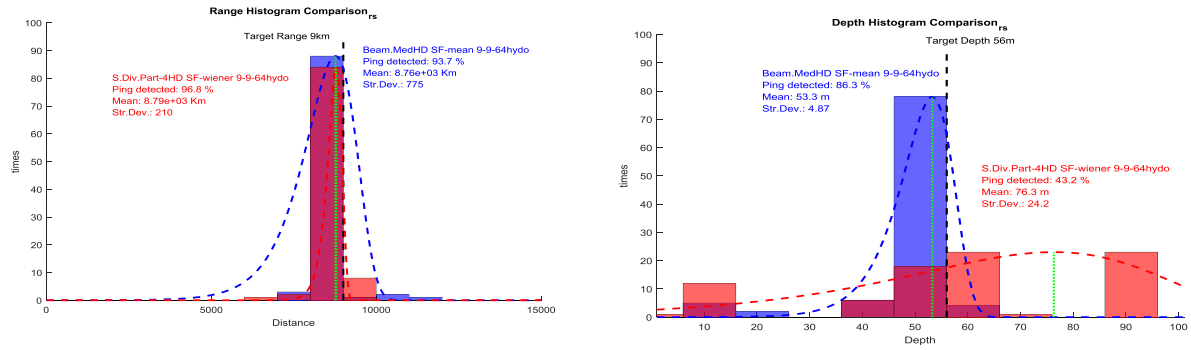


Fig. 70. Histogram of the MedHD from the direction of simulated to received, in range (left) and in depths (right)

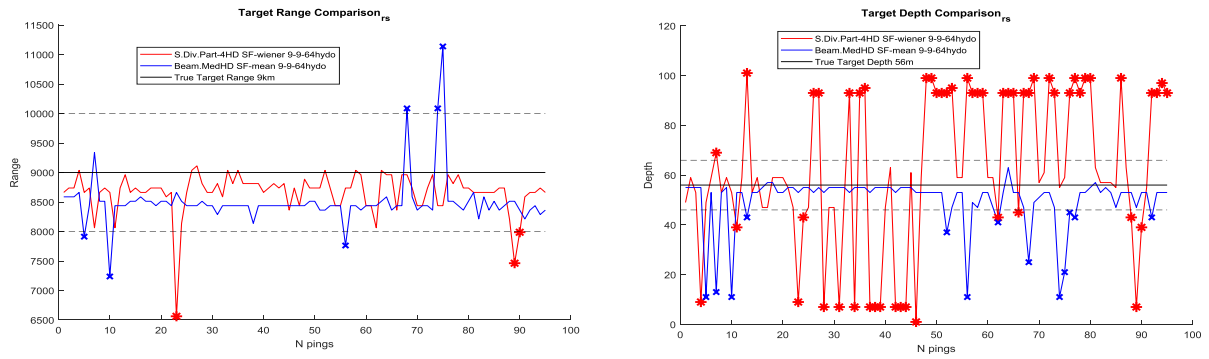


Fig. 71. Variation of the detected range (left) and detected depth (right) from the direction of received to simulated: best configuration to the Spatial diversity with SF disk 9-by-9 (red line), best configuration to the beamforming with SF mean 9-by-9 (blue line).

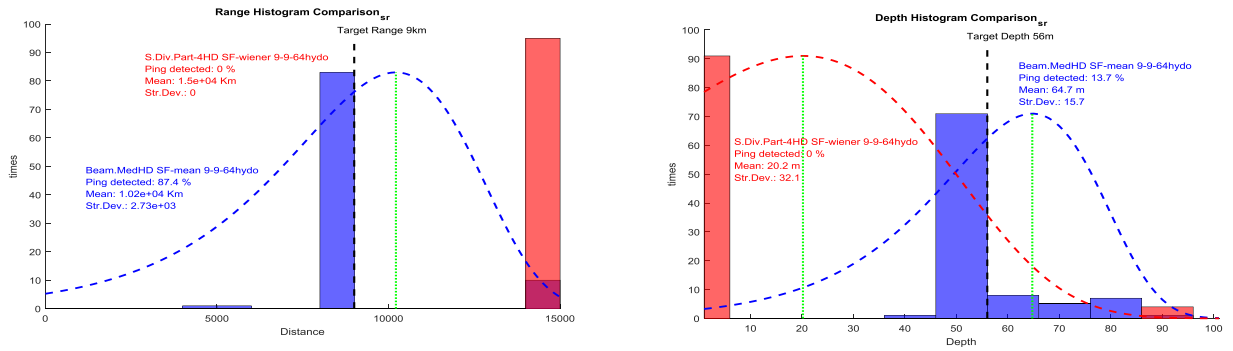


Fig. 72. Histogram of the MedHD from the direction of simulated to received, in range (left) and in depths (right).

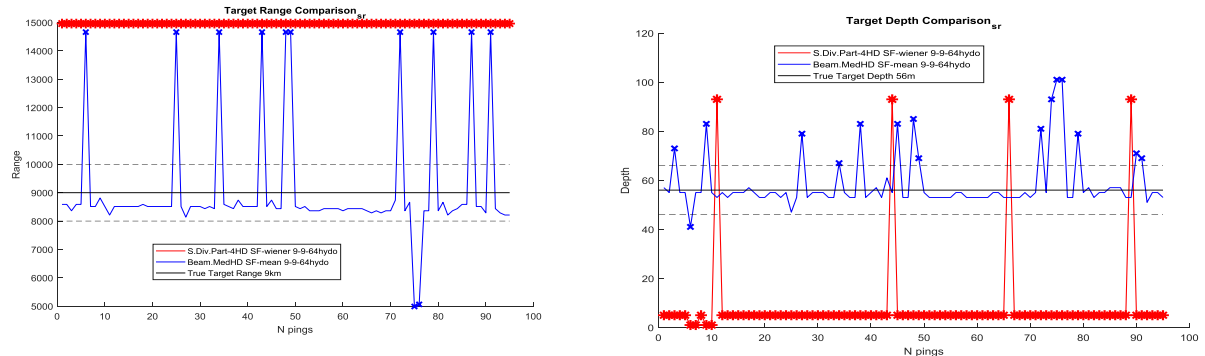


Fig. 73. Variation of the detected range (left) and detected depth (right) from the direction of simulated to received: best configuration to the Spatial diversity with SF disk 9-by-9 (red line), best configuration to the beamforming with SF mean 9-by-9 (blue line).

6.4. Minimal number of Hydrophones.

In order to find the minimal number of hydrophones, table XIV shows the variation of the number of hydrophones on the array from 64 to 32, 16, 8, 4 and finally 2 hydrophones for the SSP close to the source, with the first section used for range detection and second section for depth detection.

Table XIV .Percentage of pings detected with maximal error from the true position up to 1km in range and 10 m in **depth**. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

SSP close to the source – range detection								
	Forward HD				Backward HD			
	MedHD		MedHD		MedHD		MedHD	
	No SF		SF Mean 9-9		No SF		SF Mean 9-9	
Array 64 Hydrophones (from hydrophone 1 to 64)	79%	Red.	84%	Red.	91%	Red.	91%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	74%	-6.67%	82%	-2.50%	92%	1.16%	92%	1.16%
Array 16 Hydrophones (from hydrophone 1 to 64)	78%	-1.33%	83%	-1.25%	85%	-5.81%	85%	-5.81%
Array 8 Hydrophones (from hydrophone 1 to 64)	71%	-10.67%	77%	-8.75%	89%	-1.16%	86%	-4.65%
Array 4 Hydrophones (from hydrophone 1 to 64)	54%	-32.00%	49%	-41.25%	77%	-15.12%	61%	-32.56%
Array 2 Hydrophones (from hydrophone 1 to 64)	22%	-72.00%	20%	-76.25%	33%	-63.95%	22%	-75.58%
SSP close to the source – depth detection								
	Forward HD				Backward HD			
	MedHD		MedHD		MedHD		MedHD	
	No SF		SF Mean 9-9		No SF		SF Mean 9-9	
Array 64 Hydrophones (from hydrophone 1 to 64)	75%	Red.	82%	Red.	78%	Red.	91%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	78%	4.23%	79%	-3.85%	85%	9.46%	89%	-1.16%
Array 16 Hydrophones (from hydrophone 1 to 64)	81%	8.45%	89%	8.97%	83%	6.76%	89%	-1.16%
Array 8 Hydrophones (from hydrophone 1 to 64)	68%	-8.45%	80%	-2.56%	81%	4.05%	88%	-2.33%
Array 4 Hydrophones (from hydrophone 1 to 64)	32%	-57.75%	36%	-56.41%	64%	-17.57%	61%	-32.56%
Array 2 Hydrophones (from hydrophone 1 to 64)	8%	-88.73%	3%	-96.15%	44%	-43.24%	45%	-50.00%

Table XV shows the variation of the number of hydrophones for the SSP close to the receiver, with again the first section used for range detection and second section for depth detection.

Table XV .Percentage of pings detected with maximal error from the true position up to 1km in range and 10 m in **depth**. The **SSP used was measured close to the receiver** and the HD was applied from the direction of **received to simulated** (Forward direction) and **simulated to received** (backward direction).

SSP close to the receiver – range detection								
	Forward HD				Backward HD			
	MedHD		MedHD		MedHD		MedHD	
	No SF		SF Mean 9-9		No SF		SF Mean 9-9	
Array 64 Hydrophones (from hydrophone 1 to 64)	91%	Red.	94%	Red.	61%	Red.	87%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	92%	1.16%	94%	0.00%	59%	-3.45%	89%	2.41%
Array 16 Hydrophones (from hydrophone 1 to 64)	95%	4.65%	95%	1.12%	57%	-6.90%	87%	0.00%
Array 8 Hydrophones (from hydrophone 1 to 64)	87%	-3.49%	91%	-3.37%	67%	10.34%	95%	8.43%
Array 4 Hydrophones (from hydrophone 1 to 64)	77%	-15.12%	71%	-24.72%	33%	-46.55%	55%	-37.35%
Array 2 Hydrophones (from hydrophone 1 to 64)	36%	-60.47%	27%	-70.79%	5%	-91.38%	17%	-80.72%
SSP close to the receiver – depth detection								
	Forward HD				Backward HD			
	MedHD		MedHD		MedHD		MedHD	
	No SF		SF Mean 9-9		No SF		SF Mean 9-9	
Array 64 Hydrophones (from hydrophone 1 to 64)	75%	Red.	86%	Red.	49%	Red.	83%	Red.
Array 32 Hydrophones (from hydrophone 1 to 64)	78%	4.23%	89%	3.66%	46%	-6.38%	82%	-1.27%
Array 16 Hydrophones (from hydrophone 1 to 64)	83%	11.27%	89%	3.66%	44%	-10.64%	82%	-1.27%
Array 8 Hydrophones (from hydrophone 1 to 64)	66%	-11.27%	77%	-10.98%	53%	6.38%	80%	-3.80%
Array 4 Hydrophones (from hydrophone 1 to 64)	43%	-42.25%	54%	-37.80%	29%	-40.43%	64%	-22.78%
Array 2 Hydrophones (from hydrophone 1 to 64)	21%	-71.83%	29%	-65.85%	4%	-91.49%	22%	-73.42%

The result for an 8 hydrophones array in both SSP after applied the spatial filtering are still able to correct localize in average more than 80% of the total amount of transmitted pings. The total number of hydrophone less than 8 is not recommended due to a limited final precision, being able to localize an average less than 50% of the total number of pings.

6.5. Best Configuration

The most robust HD variants over all 4 SSP using beamforming was the MedHD, shown at Fig. 74 and for the spatial diversity was the Partial-2HD, shown at Fig. 75. The best result from the beamforming was using the SSP close to the receiver with only 6 pings detected with more than 1km limit error in range, against 8 pings for the spatial diversity using the same SSP. The best result from the spatial diversity came from using the SSP close to the source with all the pings detected in range within 1km limit error, against 15 pings for the beamforming using the same SSP detected with more than 1km limit error. For the depth detection the beamforming present better results to all different SSP, having the best result using the SSP close to the source simulated by the X.Program with the MeanHD detecting all the ping within the 10m limit error (See appendix G). Although the direction from the simulated to received presents similar results over 3 SSP, the result from the SSP close to the source simulated by X.program presents the worst detection over all cases, reason for not be used. (See appendix G).

On Fig. 74 the first 50 pings present a better accuracy in range detection compared with the last 45 pings due to the decoherence between hydrophones. The error inside the black ellipsoid trend to happen independent of the SSP to the same ping, which is different from the pattern for the spatial diversity (Fig. 75), where error from different SSP occurs in different pings. One possible explanation for error on the same ping number along different SSP is the problem of aligning between sequences, since that the TDOA received was the same to all different TDOA modelled. The Adaptive peak detection was limited to 6 interactions. Further studies need to be performed increasing the number of interactions to be compared with this result. On Fig. 76 is presented the variation of the detected depth versus ping number.

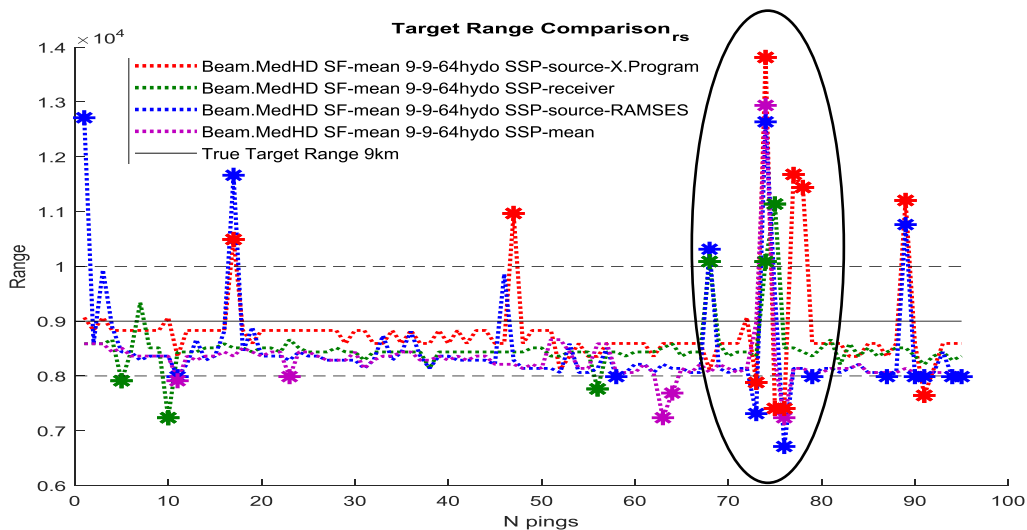


Fig. 74. Variation of the detected range for the beamforming from the direction of received to simulated using all 4 SSP.

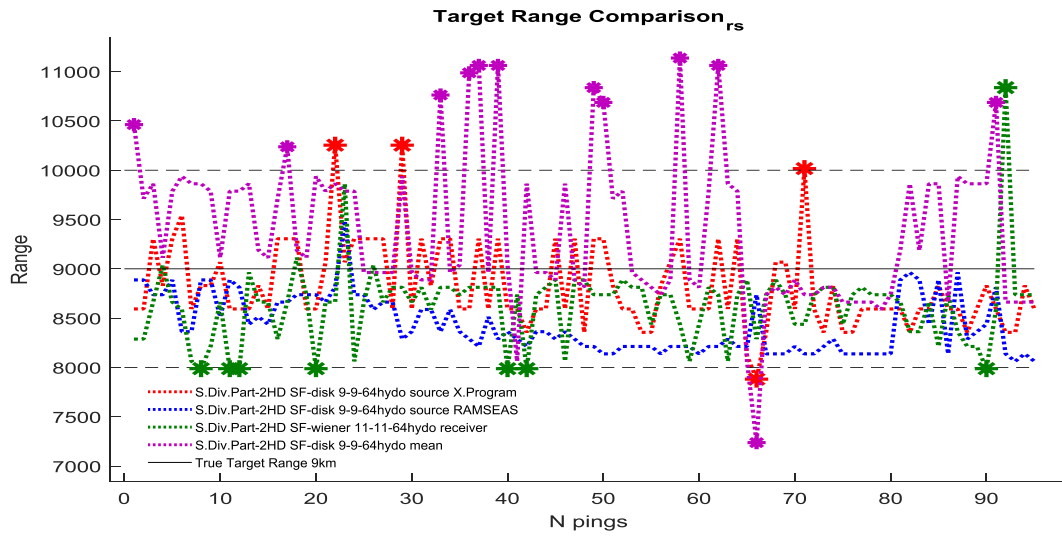


Fig. 75. Variation of the detected range for the Spatial diversity from the direction of received to simulated using all 4 SSP.

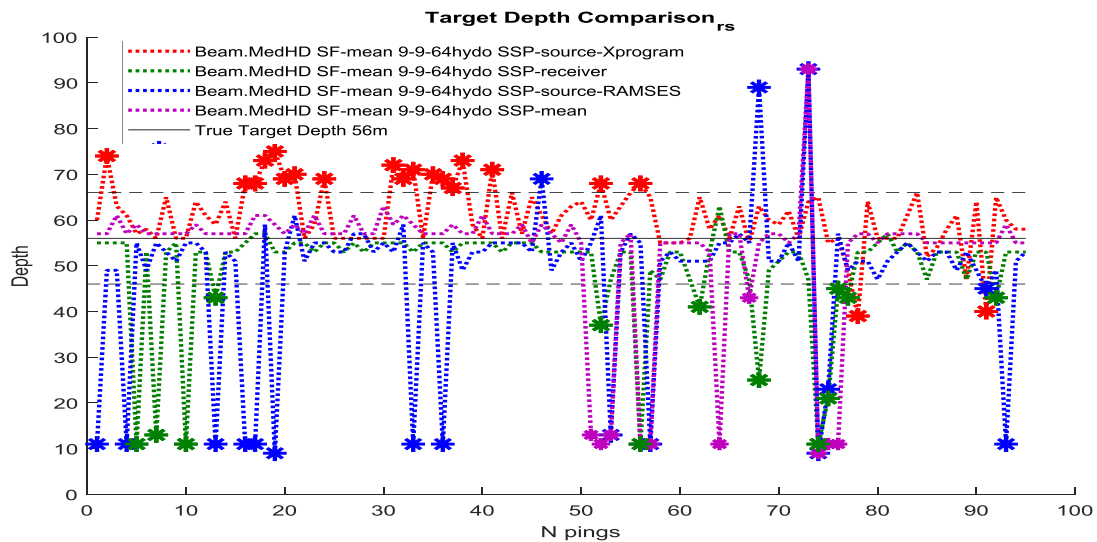


Fig. 76. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

6.6. Cramer Rao bound

The Cramer Rao bound was performed by Dr. Xavier and the best HD variants results with the correspondent spatial filtering is presented to each SSP. The Cramer Rao Bound shows the lower bound (minimal variance represented by the red ellipsoid. 50% small one and 90% big one) given the conditions of the experiment. It was performed based on deterministic functions. The chosen variants to the beamforming were from the direction received to simulated: MedHD SF mean 9-by-9, MedHD SF disk 9-by-9 and MeanHD SF disk 9-by-9. From the backward HD only two first variants were presented. For the spatial diversity considering the forwards direction: Partial4-HD SF wiener 11-by-11, Partial4-HD SF disk 9-by-9 and Partial2-HD SF disk 9-by-9. The only exception to this case was considering the SSP mean where it was included the Partial1-HD SF disk 9-by-9. To the backwards direction: Partial4-HD SF wiener 11-by-11 and MedHD SF mean 9-by-9. Fig. 77 to Fig. 84.

6.6.1 SSP close to the receiver

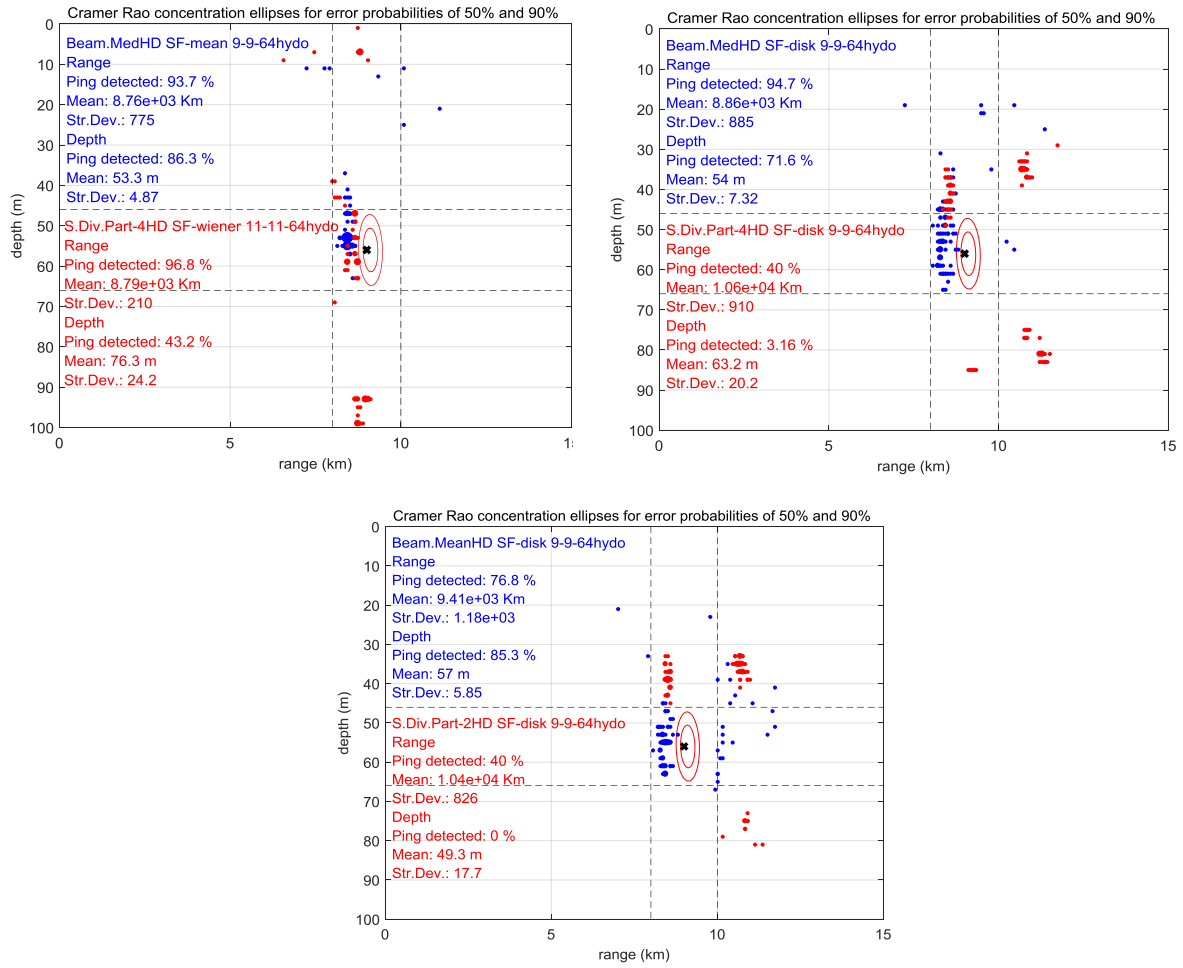


Fig. 77. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

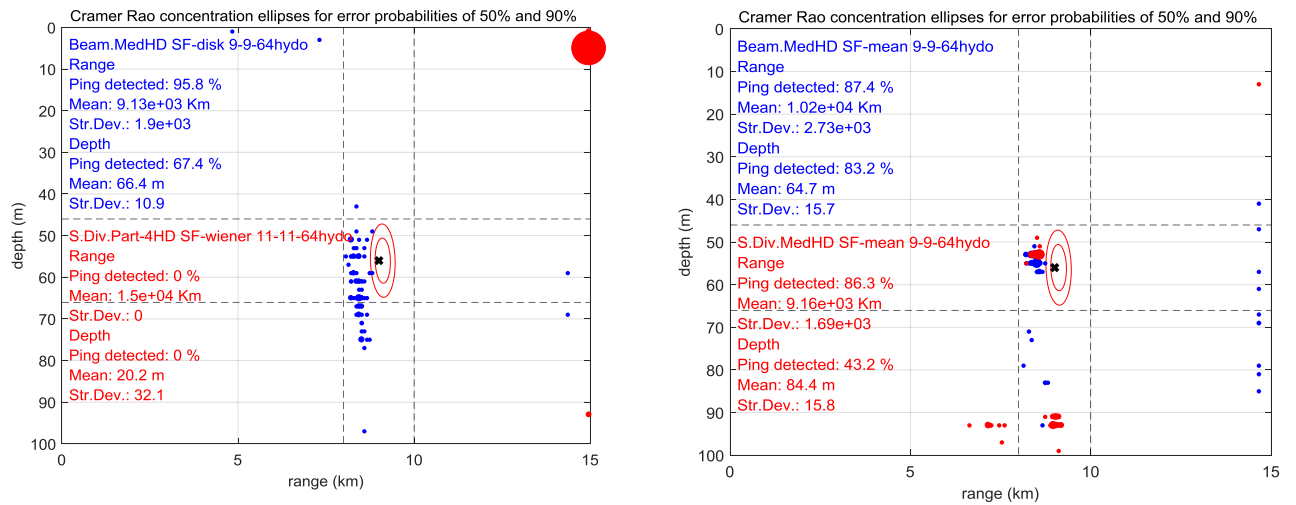


Fig. 78. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

6.6.2 SSP close to the source RAMSEAS

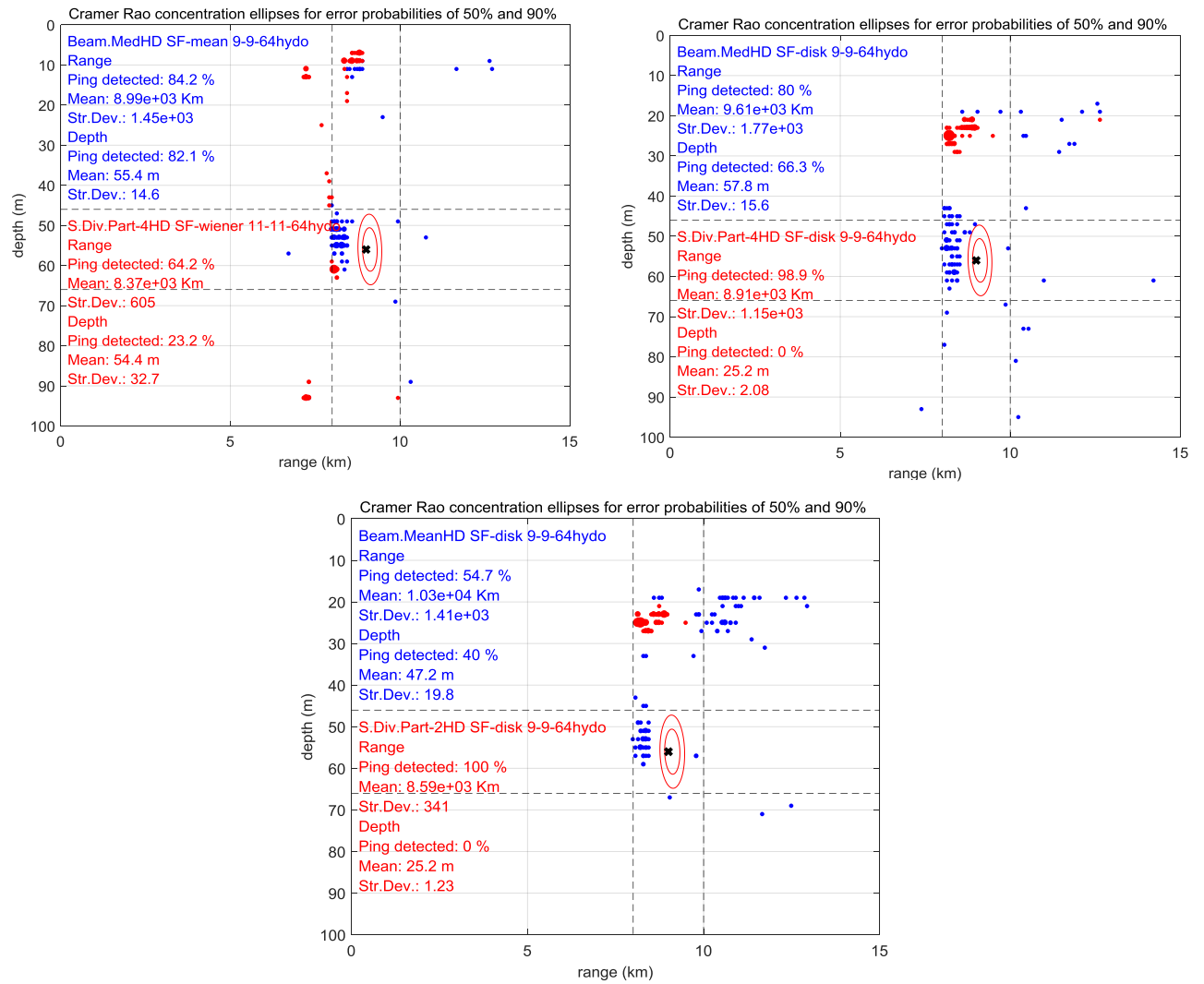


Fig. 79. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

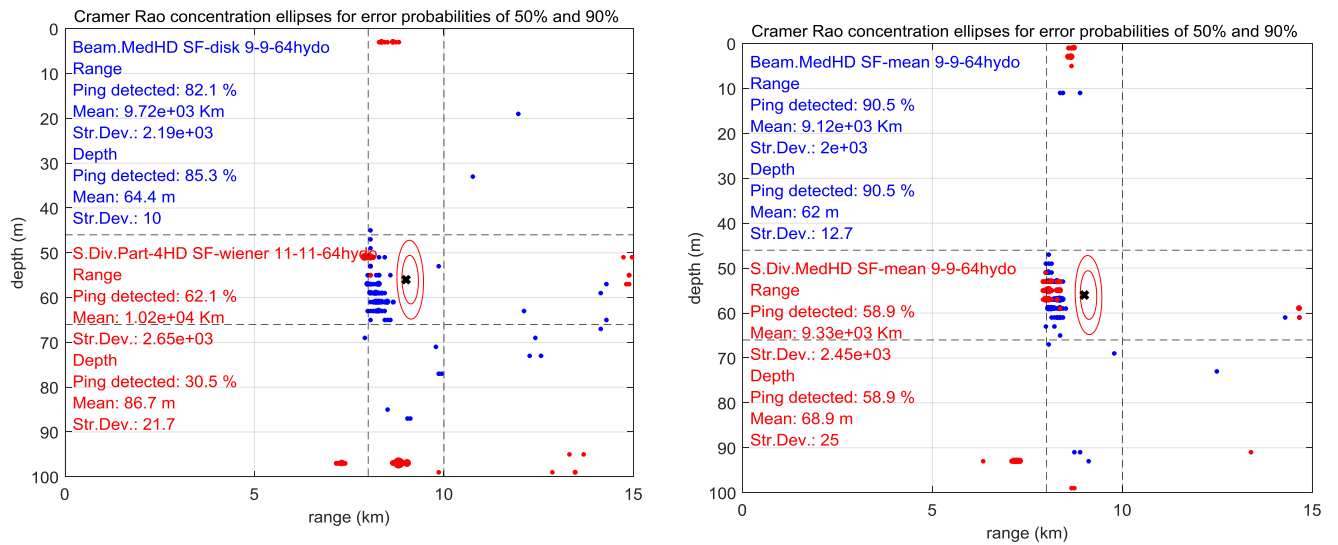


Fig. 80. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

6.6.3 SSP close to the source X.program

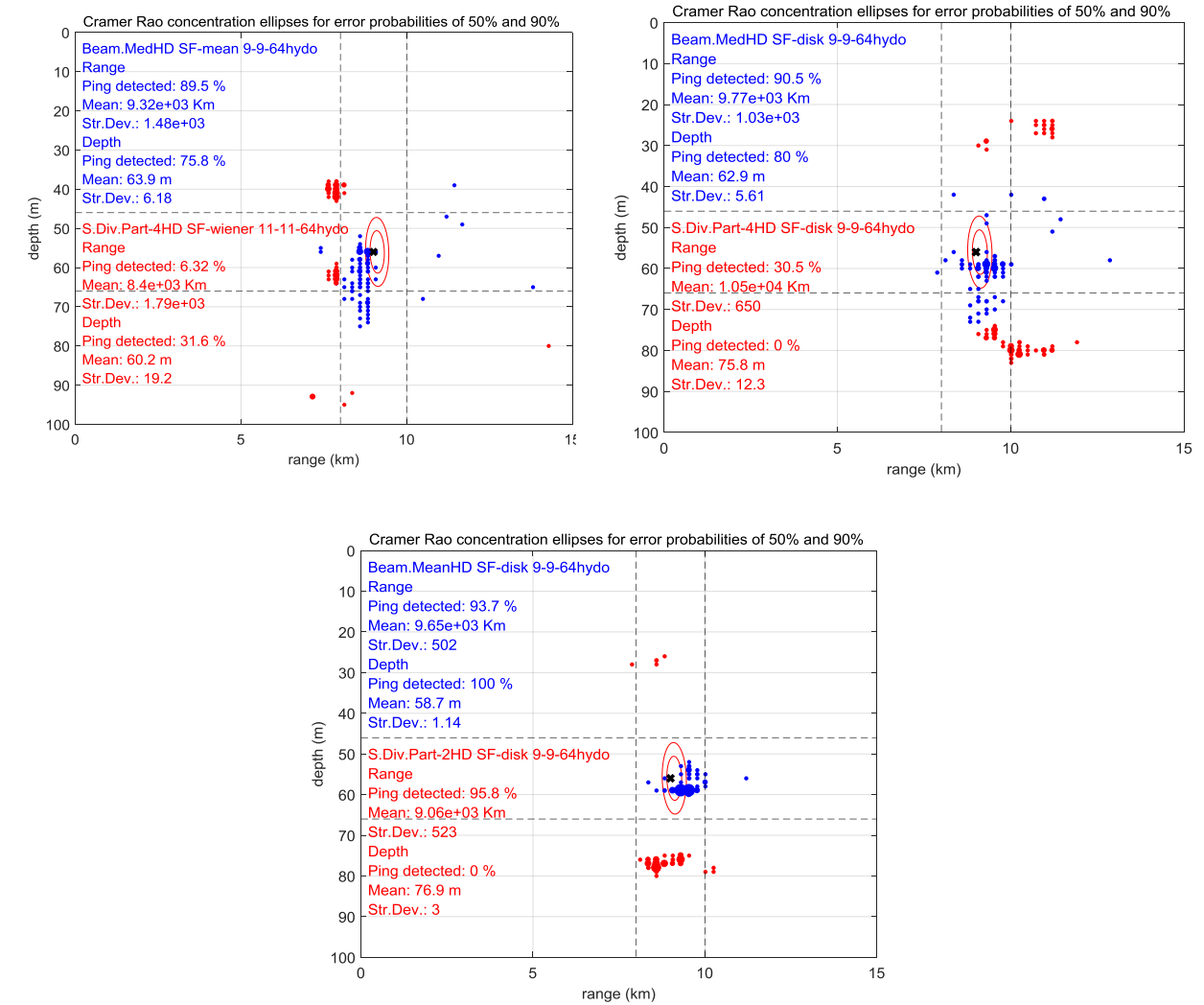


Fig. 81. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

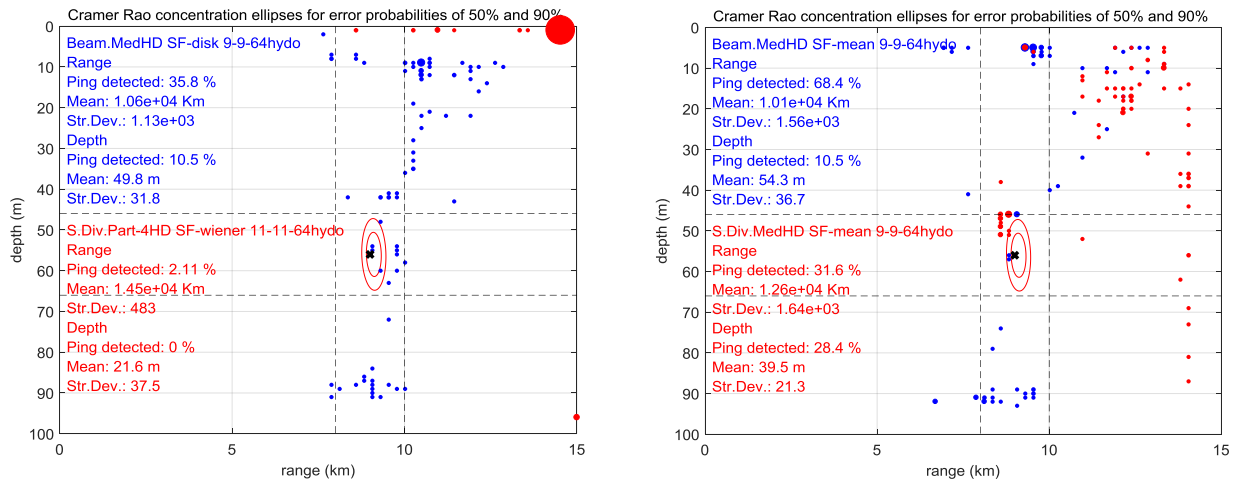


Fig. 82. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

6.6.4 SSP mean

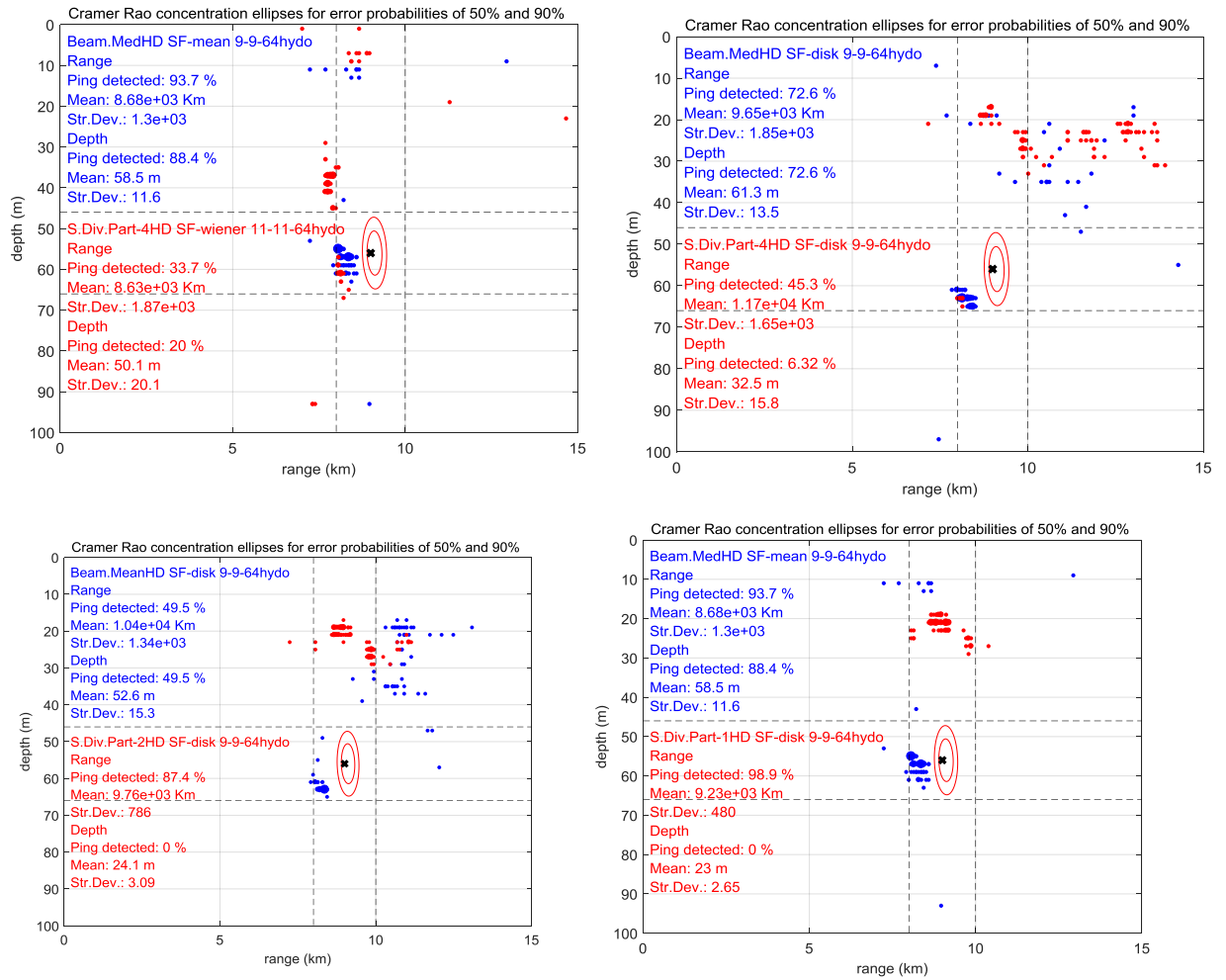


Fig. 83. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

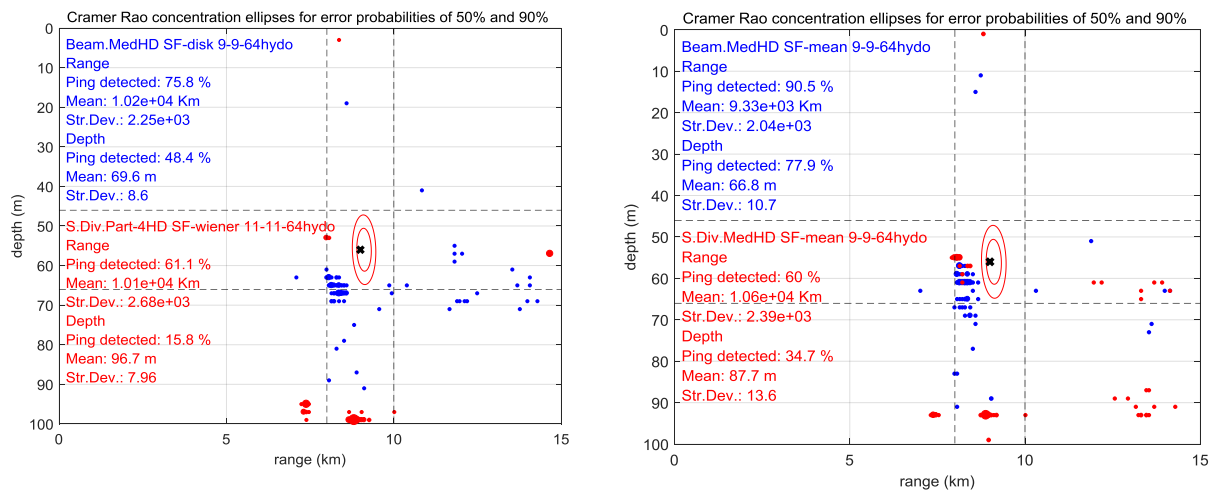


Fig. 84. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

The best overall results was found on the spatial diversity using the SSP close to the source modelled by the program RAMSEAS, considering the Partial2-HD disk 9-by-9 (red color at the Fig. 85 on the left). Although this case is the one with the small value of variance in range, it presents a bias in depths. For the beamforming the best result was found using the SSP close to the source modelled the X.program, considering the MeanHD SF disk 9-by-9 (blue color at the Fig. 85 on the right).

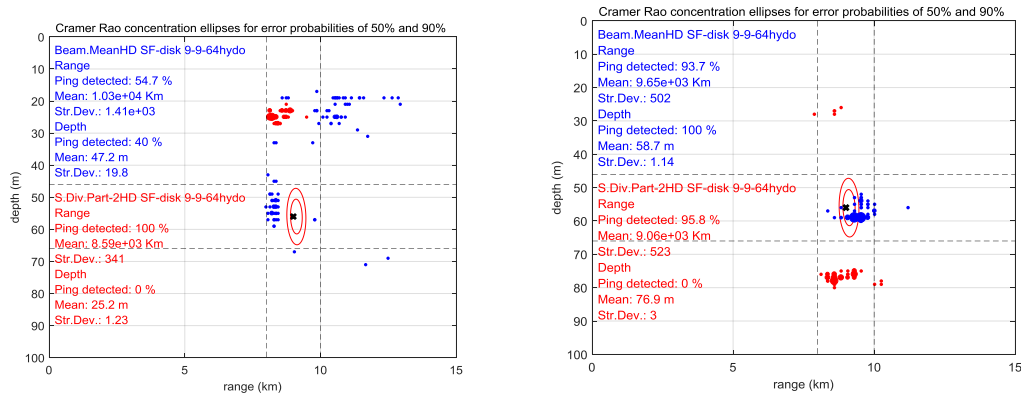


Fig. 85. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

6.7. Array Section

The last analysis was performed considering a section of the total array. This result is important because allows to define the best technique and HD variant which will be implemented in an operational vessel due to the limitation to the size of the array. The total array was divided in 3 sections each section with a 3m length. The results are presented on table XVI and XVII.

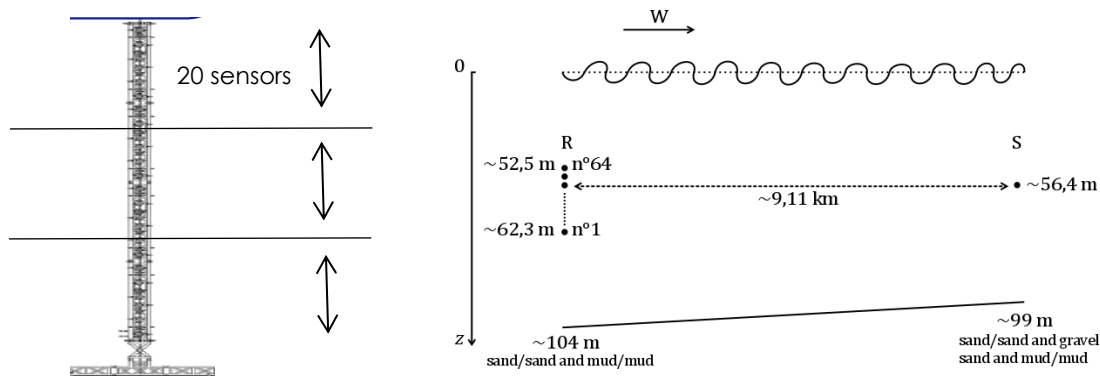


Fig. 86. Variation of the detected depth for the beamforming from the direction of received to simulated using all 4 SSP.

Table XVI .Percentage of pings detected with maximal error from the true position up to 1km in range and 10 m in **depth**. The received array was divided in 3 sub-arrays and it was tested with all 20 hydrophones and with 10 hydrophones equally spaced for the case of beamforming and equally spaced from 20, 10, 4 and 2 for the spatial diversity. The **SSP used was measured close to the source** and the HD was applied from the direction of **received to simulated** (Forward direction).

Table XVII .Percentage of pings detected with maximal error from the true position up to 1km in range and 10 m in **depth**, tested to 3 sub-arrays. The **SSP used was measured close to the receiver** and the HD was applied from the direction of **received to simulated** (Forward direction).

% detection in range with accepted error up to 1km (SSP close to the source)									
HD direction received to simulated (Forward HD)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	27%	38%	67%	45%	51%	44%	43%
		10 Hydrophones	26%	43%	67%	46%	53%	47%	45%
	Spatial diversity SF disk [9 9]	20 Hydrophones	72%	95%	48%	20%	69%	91%	96%
		10 Hydrophones	73%	94%	44%	18%	72%	91%	95%
		4 Hydrophones	76%	91%	38%	17%	58%	76%	88%
		2 Hydrophones	77%	85%	35%	16%	52%	69%	81%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	39%	31%	64%	34%	37%	29%	29%
		10 Hydrophones	34%	34%	65%	36%	35%	35%	35%
	Spatial diversity SF disk [9 9]	20 Hydrophones	80%	95%	66%	25%	83%	95%	97%
		10 Hydrophones	82%	95%	63%	24%	79%	92%	96%
		4 Hydrophones	83%	93%	51%	29%	71%	91%	95%
		2 Hydrophones	83%	86%	40%	21%	53%	71%	78%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	41%	36%	63%	53%	39%	35%	33%
		10 Hydrophones	39%	38%	58%	51%	37%	38%	37%
	Spatial diversity SF disk [9 9]	20 Hydrophones	77%	93%	77%	18%	83%	97%	98%
		10 Hydrophones	72%	95%	74%	24%	79%	94%	99%
		4 Hydrophones	79%	92%	63%	26%	76%	86%	89%
		2 Hydrophones	79%	91%	55%	23%	66%	82%	91%
% detection in depth with accepted error up to 10m (SSP close to the source)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	3%	40%	76%	27%	53%	47%	45%
		10 Hydrophones	2%	41%	77%	26%	55%	49%	44%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	1%	29%	2%	0%	0%
		10 Hydrophones	0%	0%	2%	31%	2%	0%	0%
		4 Hydrophones	0%	0%	2%	27%	2%	0%	0%
		2 Hydrophones	0%	0%	4%	19%	1%	1%	0%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	4%	27%	74%	35%	39%	33%	29%
		10 Hydrophones	3%	32%	73%	29%	42%	38%	37%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	1%	25%	0%	0%	0%
		10 Hydrophones	0%	0%	1%	25%	0%	0%	0%
		4 Hydrophones	0%	0%	1%	31%	1%	0%	0%
		2 Hydrophones	0%	0%	2%	27%	0%	0%	0%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	3%	28%	77%	33%	40%	35%	32%
		10 Hydrophones	2%	26%	77%	31%	37%	35%	31%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	0%	37%	0%	0%	0%
		10 Hydrophones	0%	0%	0%	41%	0%	0%	0%
		4 Hydrophones	0%	0%	0%	41%	0%	0%	0%
		2 Hydrophones	0%	0%	2%	38%	0%	0%	0%

% detection in range with accepted error up to 1km (SSP close to the receiver)									
HD direction received to simulated (Forward HD)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	55%	69%	77%	32%	71%	68%	68%
		10 Hydrophones	51%	71%	86%	35%	64%	64%	68%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	23%	66%	75%	46%	81%	79%	69%
		10 Hydrophones	25%	64%	69%	47%	82%	77%	66%
		4 Hydrophones	31%	56%	69%	43%	74%	73%	63%
		2 Hydrophones	37%	48%	48%	29%	57%	62%	58%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	54%	57%	79%	37%	60%	57%	56%
		10 Hydrophones	45%	56%	83%	41%	62%	58%	58%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	20%	74%	76%	44%	82%	81%	79%
		10 Hydrophones	20%	76%	77%	44%	79%	79%	78%
		4 Hydrophones	19%	63%	66%	53%	78%	75%	73%
		2 Hydrophones	36%	59%	58%	45%	65%	71%	67%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	54%	61%	86%	36%	53%	52%	54%
		10 Hydrophones	52%	59%	83%	38%	57%	56%	58%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	36%	84%	82%	42%	88%	87%	87%
		10 Hydrophones	38%	84%	74%	47%	82%	85%	84%
		4 Hydrophones	39%	79%	69%	39%	80%	77%	78%
		2 Hydrophones	48%	66%	56%	32%	71%	76%	74%
% detection in depth with accepted error up to 10m (SSP close to the receiver)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	39%	71%	84%	42%	80%	73%	71%
		10 Hydrophones	41%	72%	88%	46%	78%	73%	75%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	5%	15%	40%	36%	48%	45%	25%
		10 Hydrophones	9%	13%	36%	36%	48%	46%	27%
		4 Hydrophones	14%	11%	34%	36%	45%	37%	26%
		2 Hydrophones	16%	24%	29%	24%	39%	37%	28%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	46%	60%	86%	38%	72%	69%	66%
		10 Hydrophones	48%	56%	85%	36%	78%	72%	69%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	3%	15%	23%	22%	22%	16%	17%
		10 Hydrophones	3%	14%	24%	23%	23%	16%	14%
		4 Hydrophones	2%	11%	17%	38%	23%	21%	19%
		2 Hydrophones	13%	18%	21%	44%	32%	25%	24%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	31%	59%	87%	39%	65%	65%	60%
		10 Hydrophones	31%	59%	81%	37%	72%	66%	61%
	Spatial diversity SF wiener [11 11]	20 Hydrophones	12%	26%	29%	14%	28%	25%	27%
		10 Hydrophones	17%	24%	24%	17%	21%	31%	27%
		4 Hydrophones	11%	21%	22%	18%	23%	22%	20%
		2 Hydrophones	4%	14%	17%	19%	25%	27%	20%

. The results from the SSP close to receiver, considering the sub-array with around 3 m high, presents similar performance for range detection while for depth detection presents a better performance for the beamforming with an average more than 100% compared with the spatial diversity. The results from the remaining SSPs show that the spatial diversity has a better performance (an average 30% of improvement) compared with the beamforming for the detection in range, while the beamforming has a better performance (an average 200%) compared with the spatial diversity for the detection in depth.

6.8. Chapter Summary

In this chapter it was presented the results of using the beamforming technique. The comparison with the spatial diversity shows that the beamforming has similar performance in range while presents a big improvement to the detection in depth considering the full array size of 10 m high. The best result was found using the SSP close to the source modelled by the X.program using the MeanHD SF disk 9-by-9. The second conclusion is that once the full array was divided in 3 equal sections, each of then with 3 m high, the beamforming kept similar performance only to the case where it was used the SSP close to the receiver, being an average detected more than 80% of the ping under 1km error. To all others SSPs the use of beamforming came with a reduction in performance from around 30% in range compared with spatial diversity.

CHAPTER 7

Conclusion & Perspectives

In particular, this thesis was focused mainly on solving the inverse problem by using the Hausdorff Distance as a cost function to find the expected target location. The Hausdorff Distance was applied in two different scenarios: first in a controlled environment experiment, and second in an at-sea environment with the ALMA 2015 experiment.

From the theoretical contribution of this work, the Hausdorff distance was adapted to be used to underwater localization as well as the development of two methods using the Spatial diversity and beamforming which makes the techniques more robust against interference.

The results found are more than satisfactory and allowed the Navy to localize vessels in an operational environment.

Future work

Future work should consist of the following extensions to the presented initial trial:

- Testing other variants of the HD, particularly the Gromov-Hausdorff distance;
- Making use of not only arrival times, but also and simultaneously times and angles, plus Doppler shifts for realistic moving targets;
- Testing the HD techniques in a fully passive non-cooperative context, i.e. working with the auto-correlation or estimating the transmitted signal and comparing TDOA sequences involving all pairs of arrivals.
- Testing the HD techniques with statistically stationary, random noise (cavitation), radiated from a vessel.
- Combining the spatial diversity technique with beamforming technique.

Bibliography

- [1] C. CSW, «Prospective Operations in Confined and Shallow Waters,» Kiel , 2015.
- [2] R. G. S. A. G. R. THOMPSON, «NAVAL SERVICE ROLES AND MISSIONS IN LITTORAL WARFARE,» Johns Hopkins APL Technical Digest, Volume 14, Number 2, 1993.
- [3] P. C. Etter, «Review of Ocean-Acoustic Models,» *MTS*, 2009.
- [4] J. M. Moura et I. M. Lourtie, «Acoustic Signal Processing for Ocean Exploration».
- [5] P. C. Etter, *Underwater Acoustic Modeling and Simulation* 5th, 2018.
- [6] P. C. Etter, «Advanced Applications for Underwater Acoustic Modeling,» *Advances in Acoustics and Vibration*, 2012.
- [7] F. B. Jensen, W. A. Kuperman, M. B. Porter et H. Schmidt, *Computational Ocean Acoustics*.
- [8] D. Hertz, «Time delay estimation by combining efficient algorithms and generalized cross-correlation methods,» *IEEE Transactions on Acoustics, Speech, and Signal Processing*, pp. 1-7, 1986.
- [9] J. Hassab et R. Boucher, «Optimum estimation of time delay by a generalized correlator,» *IEEE Transactions on Acoustics, Speech, and Signal Processing*, pp. 373-380, 1979.
- [10] C. Knapp et G. Carter, «The generalized correlation method for estimation of time delay,» *IEEE Transactions on Acoustics, Speech, and Signal Processing*, pp. 320-327, 1976.
- [11] Z.-H. Michalopoulou, «Estimating the Impulse Response of the Ocean: correlation Versus Deconvolution».
- [12] A. Quazi, «An overview on the time delay estimate in active and passive systems for target localization,» *IEEE Transactions on Acoustics, Speech, and Signal Processing*, pp. 527-533, 1981.
- [13] A. Ingham, *Hydrography for the Surveyor and Engineer*. 3rd Edn., London: Blackwell Scientific Publications,, 1992.
- [14] W. Wilson, «Equation for the Speed of Sound In Sea Water.,» *The Journal of the Acoustical Society of America*, 1960.
- [15] C.-T. a. M. F. J. Chen, «Speed of Sound in Seawater at High Pressures.,» *The Journal of the Acoustical Society of America*, 1977.
- [16] V. A. Del Grosso, «New Equation for the Speed of Sound In Natural Waters ((with comparisons to other equations),» *The Journal of the Acoustical Society of America*, 1974.
- [17] K. Mackenzie, «Nine-term Equation for Sound Speed in the Oceans.,» *The Journal of the Acoustical Society of America*, 1981.
- [18] H. Medwin, «Speed of Sound In Water: A Simple Equation for Realistic Parameters.,» 1975.
- [19] F. Jensen et W. Kuperman, «Optimum frequency of propagation in shallow water environments.,» *J. Acoust. Soc. Am.*, 1983.
- [20] J. F. B. et W. A., *Computational Acoustics*, 2nd ed., New York: Springer., 2011.
- [21] E. Hamilton, «Geoacoustic modeling of the sea floor,» *J. Acoust. Soc. Am.*, 1980.

-
- [22] R. Gauss, R. Gragg, D. Wurmser, J. Fialkowski et R. Nero, «Broadband models for predicting bistatic bottom, surface and volume scattering strengths.,» 2002.
 - [23] J. Fridstrom, «Some statistical properties of the ambient noise in the Baltic Sea and its relation to passive sonar.,» 2015.
 - [24] V. B. Junior, «Localizacao de fontes sonoras em aguas rasas com uso de un unico array vertical de hidrofones por meio de modelagem acustica tridimensional,» 2016.
 - [25] J. C. Hassab, «Contact localization and motion analysis in the oceanic enviroment: A perspective.,» *IEEE J. Oceanic Eng.*, 1983.
 - [26] D. D. M. Pierce, «Matched field processing for underwater source location , .,» Naval Postgraduate School, California, 1989.
 - [27] C. S. Clay, «Use of arrays for acoustic transmission in a noisy ocean.,» chez *Review of Geophysics.*, 1966., pp. vol. 4(4), pp. 475-507..
 - [28] M. J. Hinich, «Maximum likelihood signal processing for a vertical array,» *J. of the Acoustical Soc. of Amer.*, vol. vol. 54(2), pp. pp. 499-503, 1973.
 - [29] G. C. Carter, «Variance bounds for passively locating an acoustic source with a symmetric line array.,» *J. of the Acoustical Soc. of Amer.*, vol. vol. 62(4), pp. pp. 922-926, 1977.
 - [30] H. P. Buckner, «Use of calculated sound fields and matched field detection to locate sound sources in shallow water,» *J. of the Acoustical Soc. of Amer.*, vol. vol. 59(2), pp. pp. 368-373, 1976.
 - [31] A. B. Baggeroer, W. A. Kuperman et a. P. N. Mikhalevsky, «An Overview of Matched Field Methods in Ocean Acoustics.,» *IEEE JOURNAL OF OCEANIC ENGINEERING*, vol. VOL. 18, OCTOBER 1993.
 - [32] R. Kelmm, «Range and depth estimation by line arrays in shallow water.,» *Signal Processing*, vol. vol. 3. , pp. pp. 333-344, 1981.
 - [33] R. G. Fizell, «Apphcahon of hgh-resolubon processing to range and depth estimation using ambiguity function methods.,» *J. Acoust Soc. Amer.*, vol. vol 82, pp. pp 606-613, 1987.
 - [34] A. B. Baggeroer, W. A. Kuperman et a. H. Schmdt, «Matched-field processing Source localizahon in correlated noise as an optimum parameter estimation problem,» *J. Acoustic Soc. Amer.*, vol. vol 83, pp. 571-587, 1988.
 - [35] E. J. Sullivan et D. Middleton, «Estimation and Detection Issues in Matched-Field Processing,» *IEEE JOURNAL OF OCEANIC ENGINEERING.*, vol. VOL 18, JULY 1993.
 - [36] E. C. Shang, C. S. Clay et a. Y. Y. Wang, «Passive harmomc source ranging in waveguides by using mode filter.,» *J Acoust Soc Amer*, vol. vol 78, pp. pp 172-175, 1985.
 - [37] Y.-T. Lin, A. E. Newhall et a. J. F. Lynch, «Low-frequency broadband sound source localization using an adaptive normal mode back-propagation approach in a shallow-water ocean,» *J. of the Acoustical Society of America.*, vol. vol 131., 2012..
 - [38] F. D. Tappert, L. Nghiem-Phu et S. C. and Daubin, «Source localization using the PE method.,» *J. Acoust. Soc. Am.* , vol. vol 78, 1985.
 - [39] P. Voltz et I.-T. and Lu, «A time-domain backpropagating ray technique for source localization.,» *J. Acoust. Soc. Am.*, vol. vol 95., p. pp 805–812., 1994..
 - [40] J. M. Ozard, «Matched field processing in shallow water for range, depth and bearing determination: Results of experiment and simulation.,» *J. of the Acoustical Soc. of*

- Amer.*, vol. vol. 86(2), pp. pp. 744-753, 1985.
- [41] R. Schmidt, «Multiple emitter location and signal parameter estimation.,» *IEEE Trans. on Antennas and Prop.*, vol. vol. 34, p. pp. 276–280, 1986.
 - [42] H. .. J. .. Whitehouse, B. .. Boashash et J. M. Speiser, «HIGH-RESOLUTION PROCESSING TECHNIQUES FOR TEMPORAL AND SPATIAL SIGNALS».
 - [43] S. M. Jesus, M. B. Porter, Y. Stephan, X. Demoulin, O. C. Rodriguez et E. M. M. F. Coelho, «Single hydrophone source localization,» *IEEE Journal of Oceanic Engineering*, pp. 337-346, 2000.
 - [44] A. B. Baggeroer et a. W. A. Kuperman, «Matched field processing: Source localization in correlated noise as an optimum parameter estimation problem,» *The Journal of the Acoustical Society of America.*, vol. vol 83:2, pp. pp 571-587 , 1988.
 - [45] H. Schmidt, A. B. Baggeroer, W. A. Kuperman et a. E. K. Scheer, «more tolerant to environmental mismatch of a deterministic nature Environmentally tolerant beamforming for high-resolution matched field processing: Deterministic mismatch,» *The Journal of the Acoustical Society of America.*, vol. vol 88, 1990.
 - [46] R. G. Fizez et S. C. Wales, «Source localization in range and depth in an Arctic environment.,» *J. of the Acoustical Soc. of Amer.*, 1985.
 - [47] M. J. Hinich et E. J. Sullivan, «Maximum likelihood passive localization using mode filtering,» *J Acoust Soc Amer.* , vol. vol 85, pp. pp 214-219., 1989.
 - [48] H. B. Riley et J. A. Tague, «Matched Field Processing: An Overview,» chez *The 24th Southeastern Symposium on System Theory and The 3rd Annual Symposium on Communications, Signal Processing Expert Systems, and ASIC VLSI Design*, 1992.
 - [49] A. M. Richardson et L. W. Nolte, «, “A posterrorr probability source localizahon in an uncertain sound speed, deep ocean environment,”,» *J Arousf Soc Amer.*, vol. vol 89 , pp. pp 2280-2284 , 1991.
 - [50] R. L. Culver et a. H. J. Camin, «Sonar signal processing using probabilistic signal and ocean environmental models.,» *Journal of the Acoustical Society of America* , 2008.
 - [51] E. K. Westwood, «Broadband matched-field source localization.,» *J. Acoust. Soc. Amer.*, vol. vol. 91, p. pp. 2777–2789, 1992.
 - [52] R. K. Brienzo et a. W. S. Hodgkiss, «Broadband matched-field processing,» *J. of the Acoustical S. of America* , vol. vol 94, 1993.
 - [53] G. J. Orris, M. Nicholas et J. S. Perkins, «The matched-phase coherent multi-frequency matched-field processor,» *The Journal of the Acoustical Society of America*, 2000.
 - [54] M. D. Collins et a. W. A. Kuperman, «Focalization: Environmental focusing and source localization.,» *The Journal of the Acoustical Society of America.*, vol. vol 90., 1991.
 - [55] J. F. Lynch, S. D. Rajan et a. G. V. Frisk, «A comparison of broadband and narrow-band modal inversions for bottom properties at a site near Corpus Christi.,» *J. of the Acoustical Soc. of Amer.*, vol. vol. 89(2), 1991.
 - [56] M. D. Collins, W. A. Kuperman et a. H. Schmidt, «Nonlinear inversion for ocean-bottom properties.,» *J. of the Acoustical Soc. ofAmer.*, 1992.
 - [57] Z. b. Y. a. H. f. Z. a. X. y. G. a. N. R. Chapman, «Time-Reversal Mirror-Virtual Source Array Method for Acoustic Imaging of Proud and Buried Targets,» *IEEE Journal of Oceanic Engineering*, 2016.
 - [58] F. L. .. a. M. E. Y. Ahmed E. Fouda, «Imaging and Tracking of Targets in Clutter Using Differential Time-Reversal,» *Proceedings of the 5th European Conference on Antennas and Propagation (EUCAP)*.

-
- [59] Z.-H. Michalopoulou, «Matched-impulse-response processing for shallow-water localization and geoacoustic inversion,» *The Journal of the Acoustical Society of America*, 2000.
 - [60] A. Bahr, J. J. Leonard et M. F. Fallon, «Cooperative Localization for Autonomous Underwater Vehicles,» *The International Journal of Robotics Research*, 2009.
 - [61] H. Niu, E. Reeves et P. Gerstoft, «Source localization in an ocean waveguide using supervised machine learning,» 2017.
 - [62] Z. Huang, J. Xu, Z. Gong, H. Wang et Y. Yan, «Source localization using deep neural networks in a shallow water environment,» *The Journal of the Acoustical Society of America*, 2018.
 - [63] E. J. Sullivan et K. Rameau, «Passive ranging with the SNAP model.,» SACLANTCEN report SR-118, SACLANT Undersea Research Centre. , La Spezia, Italy. , 1987..
 - [64] A. Tolstoy, «Sensitivity of matched field processing to sound speed profile mismatch for vertical arrays in a deep water Pacific environment,» *J. acoust. Soc. Amer.*, vol. vol 85, pp. pp. 2394-2404, 1989.
 - [65] R. M. Hamson et R. M. Heitmeyer, «Environmental and system effects on source localization in shallow water by the matched-field processing of a vertical array,» *J. Acoust. Soc. Amer.* , vol. vol. 86. , pp. pp. 1950-1959, 1989..
 - [66] D. R. DelBalzo, C. Feuillade et M. Rowe, «Effects of water-depth mismatch on matched-field localization in shallow water.,» *J. Acoust. Soc. Amer.*, vol. vol. 83, pp. pp. 2180-2185, 1988..
 - [67] J. R. Daugherty et J. F. Lynch, «Surface wave, internal wave, and source motion effects on matched field processing in a shallow water environment.,» *J. Acoust. Soc. Amer.*, vol. vol. 87, pp. pp. 2503-2526, 1990.
 - [68] H. V. Trees, *Optimum Array Processing.*, John Wiley & Sons, 2002..
 - [69] A. Caiti, J. P. Hermand, S. M. Jesus et a. M. B. Porter, *Experimental Acoustic Inversion Methods for Exploration of the Shallow Water Environment*, 2000.
 - [70] G. J. Orris, M. Nicholas et a. J. S. P. J., «The matched-phase coherent multi-frequency matched-field Processor.,» *J. Acoust. Soc. Am.*, vol. 107 (5), 2000.
 - [71] Z. Michalopoulou, «Robust multi-tonal matched-field inversion: A coherent approach.,» *The Journal of the Acoustical Society of America*, vol. 104:1, pp. 163-170, 1998 .
 - [72] I. Capon, «High resolution frequency wavenumber spectrum analysis,» *Proc. of the IEEE*, vol. vol. 57., pp. p. 1408-1418., 1969..
 - [73] N. Kolev et a. G. Georgiev, «Sonar Model Based Matched Field Signal Processing».
 - [74] A. Andreev et N. Kirov, «Word Image Matching Based on Hausdorff Distances,» chez *10th International Conference on Document Analysis and Recognition*, 2009.
 - [75] S. H. Kim et R.-H. Park, «An efficient algorithm for video sequence matching using the modified Hausdorff distance and the directed divergence,» *IEEE Transactions on Circuits and Systems for Video Technology*, pp. 592-596, 2002.
 - [76] X. S. X. Z. a. W. H. A. Wang, «Difference Squared Hausdorff Distance based medical image registration.,» chez *Chinese Control and Decision Conference (CCDC)*, Mianyang, 2011, 2011.
 - [77] R. & A. J. Bouslimi, «Using Hausdorff Distance for New Medical Image Annotation,» *International Journal of Database Management Systems*, 2012.
 - [78] J. B. S. a. J. H. C. Y. H. Ji, «Outdoor mobile robot localization using Hausdorff distance-based matching between COAG features of elevation maps and laser range

- data,» chez *11th International Conference on Control, Automation and Systems*, Gyeonggi-do, South Korea, 2011.
- [79] P. Bustos, F. Donoso, A. Guesalaga et M. Torres, «Matching Radar and Satellite Images Employing the Hausdorff Distance for Ship Positioning and Trajectory Estimation,» chez *2006 International Conference on Image Processing*, Atlanta, 2006.
- [80] M. Torres-Torrit et A. Guesalaga, «Automatic ship positioning and radar biases correction using the hausdorff distance,» chez *10th International Conference on Information Fusion*, Quebec, 2007 .
- [81] H. Peyvandi, B. Fazaefar et H. Amindavar, «Determining class of underwater vehicles in passive sonar using hidden Markov model with Hausdorff similarity measure,» chez *Proceedings of 1998 International Symposium on Underwater Technology*, Tokyo, 1998.
- [82] T. L. Hemminger et Y.-H. Pao, «Detection and classification of underwater acoustic transients using neural networks,» *IEEE Transactions on Neural Networks*, pp. 712-718, 1994.
- [83] S. Reed, Y. Petillot et J. Bell, «Automated approach to classification of mine-like objects in sidescan sonar using highlight and shadow information,» *IEE Proceedings - Radar, Sonar and Navigation*, pp. 48-56, 2004.
- [84] V. & P. M. Berinde, «The role of the Pompeiu-Hausdorff metric in fixed point theory,» *CREAT. MATH. INFORM.* , vol. 22, pp. 143-150, 2013.
- [85] A. Mours, C. Ioana, J. Mars, N. Josso et Y. Doisy, «Target-depth estimation in active sonar: Cramer-Rao bounds for a bilinear sound-speed profile,» *The Journal of the Acoustical Society of America* , 2016.
- [86] D. Pompeiu, «Sur la continuité des fonctions de variables complexes (These),» Gauthier-Villars, Paris, 1905.
- [87] F. Hausdorff, *Grundzüge der Mengenlehre*, Leipzig: Veit, 1914.
- [88] F. Hausdorff, *Mengenlehre*, Walter de Gruyter, Berlin: Zweite neubearbeitete Auflage, 1927.
- [89] b. J. R. A. F. Hausdorff. *Trans, Set theory*, New York, N. Y.: Chelsea, 1957.
- [90] Birsan, T. & Tiba et Dan, «One Hundred Years Since the Introduction of the Set Distance by Dimitrie Pompeiu.,» chez *International Federation for Information Processing Digital Library; System Modeling and Optimization*, 2005.
- [91] D. P. Huttenlocher, G. A. Klanderman et W. J. Rucklidge, «Comparing images using the Hausdorff distance,» *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 850-863, 1993.
- [92] M. P. Dubuisson et A. K. Jain, «A modified Hausdorff distance for object matching,» chez *Proceedings of 12th International Conference on Pattern Recognition*, Jerusalem, 1994.
- [93] C. F. Olson, «A probabilistic formulation for Hausdorff matching,» chez *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Santa Barbara, CA, 1998.
- [94] D. Edwards, «The Structure of Superspace,» *Studies in Topology*, Academic Press, 1975.
- [95] M. Gromov, *Structures métriques pour les variétés riemanniennes.*, Paris: J. Lafontaine and P. Pansu. Textes Mathématiques [Mathematical Texts], 1981.
- [96] A. A. Tuzhilin, «Who Invented the Gromov-Hausdorff Distance?,» 2016.

-
- [97] F. Mémoli, «On the use of Gromov-Hausdorff Distances for Shape Comparison,» chez *Symposium on Point Based Graphics*, Prague, Czech Republic., 2007.
 - [98] H. E. Zou C., *Face Recognition Using Simplicial Complexes*, Springer, Berlin, Heidelberg, 2010.
 - [99] A. M. Bronstein, M. M. Bronstein, R. Kimmel, M. Mahmoudi et G. Sapiro, «A Gromov-Hausdorff Framework with Diffusion Geometry for Topologically-Robust Non-rigid Shape Matching,» *International Journal of Computer Vision*, vol. 89, n° 12–3, p. 266–286, 2010.
 - [100] G. R. Dominique Fattaccioli, «The DGA "ALMA" Project: an overview of the recent improvements of the system capabilities and of the at-sea campaign ALMA-2016,» chez *UACE 2017*, Greece, 2017.
 - [101] W. Weichselberger et a. J. Fuhl, *Adaptive Antenna arrays*.
 - [102] G. Carter, «Time delay estimation for passive sonar signal processing,» *IEEE Transactions on Acoustics, Speech, and Signal Processing*, pp. 463-470, 1981.
 - [103] A. B. Baggeroer, W. A. Kuperman et P. N. Mikhalevsky, «An overview of matched field methods in ocean acoustics,» *IEEE Journal of Oceanic Engineering*, pp. 401-424, 1993.
 - [104] H. Schmidt, A. B. Baggeroer, W. A. Kuperman et E. K. Scheer, «Environmentally tolerant beamforming for high-resolution matched field processing: Deterministic mismatch,» *The Journal of the Acoustical Society of America*, 1990.
 - [105] N. E. Hurt, «Maximum likelihood estimation and MUSIC in array localization signal processing: A review,» *Multidimensional Systems and Signal Processing*, p. 279–325, 1989.
 - [106] J. M. Ozaard, «Matched field processing in shallow water for range, depth, and bearing determination: Results of experiment and simulation,» *The Journal of the Acoustical Society of America*, 1989.
 - [107] Q. Zhang et J. Huang, «Joint estimation of DOA and time-delay in underwater localization,» chez *IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings*, Phoenix, 1999.
 - [108] K. Kim, W. Seong et C. Lee, «Matched field processing: analysis of feature extraction method with ocean experimental data,» chez *Proceedings of the 2004 International Symposium on Underwater Technology*, 2004.
 - [109] J. Gebbie, M. Siderius, P. L. Nielsen et J. Miller, «Passive localization of noise-producing targets using a compact volumetric,» *Journal Of The Acoustical Society Of America*, pp. 80-89, 2014.
 - [110] L. Kinsler, A. Frey et A. Coppens, *Fundamentals of Acoustics*. 3 ed, New York: John Wiley & Sons, 1982.
 - [111] G. J. Orris, M. Nicholas et a. J. S. Perkins, «The matched-phase coherent multi-frequency matched-field processor.,» *J. Acoust. Soc. Amer.*, vol. vol. 107, p. pp. 2563–2575, 2000..
 - [112] T. F. Duda et J. C. and Preisig, «A modeling study of acoustic propagation through moving shallow-water solitary wave packets,» *IEEE J.Oceanic Eng.* , vol. vol 24., p. pp 16–32., 1999.
 - [113] A. M. Richardson et a. L. W. Nolte, «A posteriori probability source localization in an uncertain sound speed, deep ocean environment,» *The Journal of the Acoustical Society of America*, vol. vol 89, 1991.

- [114] D. Moreno-Salinas, A. Pascoal et J. Aranda, «Optimal Sensor Placement for Acoustic Underwater Target Positioning With Range-Only Measurements,» *IEEE Journal of Oceanic Engineering* , 2016.
- [115] U. R. J., Principles of Underwater Sound for Engineers, New York: McGraw-Hill, 1975.

Wave equation

Mathematical basis for the study of sound propagation is a representing the variation of physical quantities that have their values modified a disturbance of the equilibrium conditions of a material medium. It concentrates combined effect of three physical concepts represented by the Continuity Equation, the Movement of the equation (Euler) and the State equation

$$\frac{d(\rho)}{dt} - \nabla \cdot (\rho \vec{v}) = 0 \quad \text{Equation (0.1)}$$

$$\frac{dv}{dt} + \frac{1}{\rho_0} \left(\frac{d\Delta p}{dx} \right) = 0 \quad \text{Equation (0.2)}$$

$$\frac{d^2 p}{dx^2} - \frac{1}{c^2} \frac{d^2 p}{dt^2} = 0 \quad \text{Equation (0.3)}$$

Expanding the state's equation around the equilibrium pressure, taking the first-order terms and deriving over time we have:

$$\frac{dp}{dt} = + \left(\frac{dP_0}{d\rho_0} \right)_S \frac{d\rho}{dt} + \left(\frac{dP_0}{dS_0} \right)_\rho \frac{dS}{dt} = 0 \quad \text{Equation (0.4)}$$

where the index S and ρ , subscribed in parentheses, mean entropy and constant density.

Substituting dp/dt taken from the Equation (0.1), and dS/dt taken from **Error! Reference source not found.** is obtained:

$$\frac{dp}{dt} = + \left(\frac{dP_0}{d\rho_0} \right)_S (-\nabla \cdot (\rho_0 \vec{v})) + \left(\frac{dP_0}{dS_0} \right)_\rho (-(\vec{v} \cdot \nabla) S) = 0 \quad \text{Equation (0.5)}$$

For a fluid hydrostatic equilibrium without external forces, the pressure varies only with depth, that is $P_0 = \rho_0 gh$, therefore $(dP_0/dS_0)_\rho = 0$, the Equation (0.5) becomes:

$$\frac{dp}{dt} + \rho_0 \left(\frac{dP_0}{d\rho_0} \right)_S \nabla \cdot \vec{v} = 0 \quad \text{Equation (0.6)}$$

Deriving Equation (0.6) with respect to time we have:

$$\frac{d^2 p}{dt^2} + \rho_0 \left(\frac{dP_0}{d\rho_0} \right)_s \frac{d}{dt} \nabla \cdot v = 0 \quad \text{Equation (0.7)}$$

Given the linearity of the derivative operators and divergence:

$$\frac{d^2 p}{dt^2} + \rho_0 \left(\frac{dP_0}{d\rho_0} \right)_s \nabla \cdot \frac{dv}{dt} = 0 \quad \text{Equation (0.8)}$$

Taking the divergence of Equation (0.8) we have:

$$\begin{aligned} \nabla \left(\rho_0 \frac{dv}{dt} + \nabla p \right) &= 0 \rightarrow \nabla \cdot \left(\frac{dv}{dt} \right) + \nabla \cdot \left(\frac{1}{\rho_0} \nabla p \right) = 0 \\ &\rightarrow \nabla \cdot \left(\frac{dv}{dt} \right) = -\nabla \cdot \left(\frac{1}{\rho_0} \nabla p \right) \end{aligned} \quad \text{Equation (0.9)}$$

Substituindo Equation (0.9) em **Error! Reference source not found.**, fazendo $(dP_0/d\rho_0)_s = c^2$, onde c é a velocidade de propagação do som e rearrumando os termos chega-se a:

Substituting Equation (0.9) in Equation (0.8), where $(dP_0/d\rho_0)_s = c^2$, which is the sound velocity and rearranging the terms comes to:

$$\rho_0 \nabla \cdot \left(\frac{1}{\rho_0} \nabla p \right) - \frac{1}{c^2} \frac{d^2 p}{dt^2} = 0 \quad \text{Equation (0.10)}$$

The Helmholtz Equation

The Helmholtz equation, results from applying the technique of [separation of variables](#) to reduce the complexity of the analysis. Usually arises in the study of physical problems involving [partial differential equations](#) in both space and time.

$$\left(\nabla^2 - \frac{1}{c^2} \frac{d^2}{dt^2} \right) p(r, t) = 0 \quad \text{Equation (0.11)}$$

Assuming that the wave function $p(r, t)$ is separable, due to [linear combination](#) of [sine](#) and [cosine](#) functions (time harmonic function):

$$p = A * e^{iwt} \quad \text{Equation (0.12)}$$

Substituting this form into the wave equation, and then simplifying, we obtain the following equation

$$\rho_0 \nabla \cdot \left(\frac{1}{\rho_0} \nabla (A * e^{iwt}) \right) - \frac{w^2}{c^2} A * e^{iwt} = 0 \quad \text{Equation (0.13)}$$

Where w is the angular frequency,

$$w = kc \quad \text{Equation (0.14)}$$

As a result, we obtain the Helmholtz equation:

$$\nabla^2(p) - k^2 p = 0 \quad \text{Equation (0.15)}$$

Then, we looking for a solution of the Helmholtz equation, to obtain the ray equations, in the form, called the ray series:

$$p(x) = e^{iwt(x)} \sum_{j=0}^{\infty} \frac{A_j(x)}{(iw)^j} \quad \text{Equation (0.16)}$$

Taking derivatives of the ray series, we obtain:

$$p_x = e^{iwt} \left[iw \tau_x \sum_{j=0}^{\infty} \frac{A_j}{(iw)^j} + \sum_{j=0}^{\infty} \frac{A_{j,x}}{(iw)^j} \right] \quad \text{Equation (0.17)}$$

And the second derivative is:

$$p_{xx} = e^{iw\tau} \left\{ [-w^2(\tau_x)^2 + iw\tau_{xx}] \sum_{j=0}^{\infty} \frac{A_j}{(iw)^j} + 2iw\tau_x \sum_{j=0}^{\infty} \frac{A_{j,x}}{(iw)^j} + \sum_{j=0}^{\infty} \frac{A_{j,xx}}{(iw)^j} \right\} \quad \text{Equation (0.18)}$$

Thus, we can write in function of the gradient

$$\nabla^2(p) = e^{iw\tau} \left\{ [-w^2|\nabla_\tau|^2 + iw\nabla_\tau^2] \sum_{j=0}^{\infty} \frac{A_j}{(iw)^j} + 2iw\tau_x \sum_{j=0}^{\infty} \frac{\nabla A_j}{(iw)^j} + \sum_{j=0}^{\infty} \frac{\nabla^2 A_j}{(iw)^j} \right\} \quad \text{Equation (0.19)}$$

Substituting this result into the Helmholtz equation and equating terms of like order in w , we obtain the following infinite sequence of equations for the functions $A_j(x)$

$$\begin{aligned} O(w^2) &= |\nabla_\tau|^2 = c^{-2}(x) \\ O(w) &= 2\nabla_\tau \cdot \nabla_{A_0} + (\nabla^2 \tau) A_0 = 0 \\ O(w^{1-j}) &= 2\nabla_\tau \cdot \nabla_{A_j} + (\nabla^2 \tau) A_j = -\nabla^2 A_{j-1} \quad j = 1, 2, \dots \end{aligned} \quad \text{Equation (0.20)}$$

The $O(w^2)$ equation for $\tau(x)$ is known as the eikonal equation. The remaining equations for $A_j(x)$ are known as the transport equations.

Ray Path (Dr. Xavier Theory)

Ray acoustics is based on the assumption that sound propagates along rays that are normal to wave fronts. When generated from a point source in a medium with constant sound speed, the wave fronts form surfaces that are concentric circles, and the sound follows straight line paths that radiate out from the sound source. However the rays follow curved paths rather than straight ones if the sound speed is not constant, due to the smell's law.

The starting point of the ray tracing is given by the acoustic Unidimensional wave. In our code, the ray equations are integrated using standard numerical integrators such as the Runge–Kutta method.

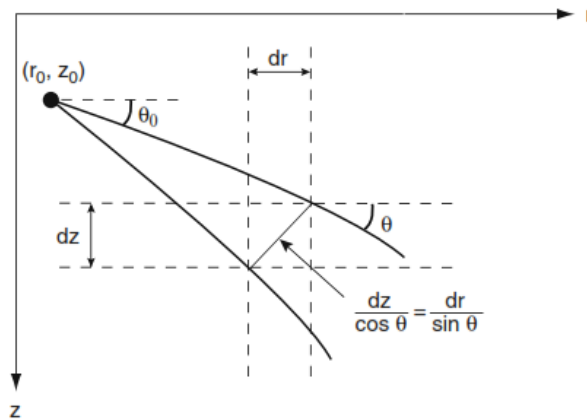


Figure 1: Ray cross section

In order to reduce the processional time we combine the solution for the Eikonal **Error! Reference source not found.** and **Error! Reference source not found.** Figure 1

$$\frac{dz/ds}{dr/ds} = \frac{dz}{dr} = \frac{\sin \theta_0}{c(0)} * \frac{c(0)}{\cos \theta_0} = \tan \theta_0 = U \quad \text{Equation (0.21)}$$

And we are interest in the X variation so we derivate U in the Equation (0.21) by $(\partial/\partial x)$

$$\frac{dU}{dx} = \frac{1}{\cos^2 \theta_0} * \frac{d\theta}{dx} \quad \text{Equation (0.22)}$$

Using the snell's law

$$\varepsilon = \frac{\cos \theta_0}{c(0)} = \frac{\cos \theta_z}{c(z)} = c^{te} \quad \text{Equation (0.23)}$$

Deriving in ε the Equation (0.23) by $(\partial/\partial x)$

$$\frac{d\varepsilon}{dx} = -\frac{\sin \theta_z}{c(z)} * \frac{d\theta}{dx} - \frac{\cos \theta_z}{c^2(z)} * \frac{dc}{dz} * \frac{dz}{dx} = 0 \quad \text{Equation (0.24)}$$

$$\frac{d\theta}{dx} = -\frac{\cos \theta_0}{\sin \theta_0} * \frac{dc}{dz} * \frac{dz}{dx} * \frac{1}{c(z)} = -\frac{1}{c(z)} * \frac{dc}{dz} \quad \text{Equation (0.25)}$$

As a result:

$$\frac{dU}{dx} = -(1 + U^2) * \frac{1}{c(z)} * \frac{dc}{dz} \quad \text{Equation (0.26)}$$

Where:

$$\frac{1}{\cos^2 \theta_0} = \frac{\cos^2 \theta_0 + \sin^2 \theta_0}{\cos^2 \theta_0} = (1 + \tan^2 \theta) = (1 + U^2) \quad \text{Equation (0.27)}$$

The initial conditions ($x=0$) for This new ordinary differential equations are:

$$z=z_S$$

$$U=\tan \theta$$

As a inicial approach we define the canonical munk sound speed profile describe by the equation:

$$c = c_0 * [1 + \epsilon * (\bar{z} - 1 + e^{-\bar{z}})] \quad \text{Equation (0.28)}$$

Where:

$$\bar{z} = 2 * \frac{z - z_{ax}}{z_{ax}} \quad \text{Equation (0.29)}$$

Initial conditions.

$$c_0 = 1500m/s$$

$$z_{ax} = 1300m$$

$$\epsilon = 7.4e^{-3}$$

Deriving the Equation (0.28) by $(\partial/\partial z)$

$$\frac{dc}{dz} = c_0 * \epsilon * \frac{d\bar{z}}{dz} * (1 - e^{-\bar{z}}) \quad \text{Equation (0.30)}$$

Where:

$$\frac{d\bar{z}}{dz} = \frac{2}{z_{ax}} \quad \text{Equation (0.31)}$$

In order to find the time arrival we have:

$$c = \frac{\Delta s}{\Delta t} \quad \text{Equation (0.32)}$$

$$\frac{dx}{dr} = \cos \theta \quad \text{Equation (0.33)}$$

$$\frac{dt}{dx} = \frac{1}{c * \cos \theta} \quad \text{Equation (0.34)}$$

Applying the Equation (0.27) in above

$$\frac{dt}{dx} = \frac{(1 + U^2)^{1/2}}{c} \quad \text{Equation (0.35)}$$

The TDOA are:

$$\tau = t - \frac{x}{c_0} \quad \text{Equation (0.36)}$$

For the distance of the ray we have:

$$\frac{dr}{dx} = (1 + U^2)^{1/2} \quad \text{Equation (0.37)}$$

The initial condition (x=0) are:

R=0

T=0

The amplitude is:

$$A = A_m * \frac{1}{x} * \frac{1}{\left| \frac{dz}{d\theta_0} \right|} \quad \text{Equation (0.38)}$$

$$\frac{dz}{d\theta_0} = \frac{dU}{d\theta_0} \quad \text{Equation (0.39)}$$

$$\frac{dU}{dx} = -(1 + \tan^2 \theta) * \frac{1}{c(z)} * \frac{dc}{dz} \quad \text{Equation (0.40)}$$

Deriving U in the Equation (0.40) by $(\partial/\partial\theta_0)$

$$\begin{aligned} \frac{dU}{d\theta_0} = & -2 * U * \frac{dU}{d\theta_0} * \frac{dc}{dz} * \frac{1}{c(z)} - (1 + U^2) * \frac{1}{c(z)} * \frac{d^2c}{dz^2} * \frac{dz}{d\theta_0} + (1 + U^2) \\ & * \frac{dc}{dz} * \frac{1}{c^2(z)} * \frac{dc}{dz} * \frac{dz}{d\theta_0} \end{aligned} \quad \text{Equation (0.41)}$$

$$\begin{aligned} \frac{dU}{d\theta_0} = & -2 * U * \frac{dU}{d\theta_0} * \frac{dc}{dz} * \frac{1}{c(z)} - (1 + U^2) \\ & * \frac{dz}{d\theta_0} \left(\frac{1}{c(z)} * \frac{d^2c}{dz^2} - \frac{1}{c^2(z)} * \left(\frac{dc}{dz} \right)^2 \right) \end{aligned} \quad \text{Equation (0.42)}$$

Deriving c in the Equation (0.28) by $(\partial/\partial z)$

$$\frac{d^2 c}{dz^2} = c_0 * \epsilon * \frac{2}{z_{ax}} * (-e^{-\bar{z}}) * \frac{2}{z_{ax}} \quad \text{Equation (0.43)}$$

The initial conditions ($x=0$):

$$\frac{dz}{d\theta_0} = 0 \quad \text{Equation (0.44)}$$

$$\frac{dU}{d\theta_0} = \frac{1}{\cos^2 \theta_0} = (1 + U^2) \quad \text{Equation (0.45)}$$

Lastly, we must restart the ray tracing each time that the boundary is reached, but with the take-off angle reflected. The appropriate conditions are:

$$\left. \frac{dz}{dx} \right|_r = \left. \frac{dz}{dx} \right|_i \quad \text{Equation (0.46)}$$

$$\left. \frac{dU}{dx} \right|_r = - \left. \frac{dU}{dx} \right|_i \quad \text{Equation (0.47)}$$

$$\left. \frac{dt}{dx} \right|_r = \left. \frac{dt}{dx} \right|_i \quad \text{Equation (0.48)}$$

$$\left. \frac{dr}{dx} \right|_r = \left. \frac{dr}{dx} \right|_i \quad \text{Equation (0.49)}$$

$$\left. \frac{dz}{d\theta_0} \right|_r = - \left. \frac{dz}{d\theta_0} \right|_i \quad \text{Equation (0.50)}$$

$$\left. \frac{dU}{d\theta_0} \right|_r = - \left. \frac{dU}{d\theta_0} \right|_i - 2 * \frac{1}{c} * \frac{dc}{dz} * \frac{1}{\tan \theta_i} * \left. \frac{dz}{d\theta_0} \right|_i \quad \text{Equation (0.51)}$$

If the index of refraction is independent of frequency, then the ray paths are also independent of frequency. However, the phase is frequency dependent. In practice, there is usually a frequency-dependent loss which adds an imaginary term to the index of refraction. This loss introduces an additional frequency dependence in the ray calculation. (Book computational)

APPENDIX D

Model of Francois and Garrison

The absorption coefficient proposed by Francois and Garrison is decomposed into three terms, The first two terms of the equation show the contribution from two relaxation processes, the third term corresponds to the viscosity of pure water:

$$\alpha(f) = A_1 P_1 \frac{f_1 f^2}{f_1^2 + f^2} + A_2 P_2 \frac{f_2 f^2}{f_2^2 + f^2} + A_3 P_3 f^2 \quad \text{Equation (52)}$$

Where $\alpha(f)$ is the attenuation, in dB/km, Z is the depth, S is the salinity, T is the temperature, in °C, and f is the frequency, in kHz.

The boric acid $B(OH)_3$ contribution is quantified by

$$\begin{aligned} A_1 &= \frac{8.86}{c} 10^{(0.78pH-5)} \\ P_1 &= 1 \\ f_1 &= 2.8 \sqrt{\frac{S}{35}} 10^{\left(4 - \frac{1245}{T+273}\right)} \\ c &= 1412 + 3.21T + 1.19S + 0.0167Z \end{aligned} \quad \text{Equation (53)}$$

In the above, c is the speed of sound in m/s under the water, which is approximately and T_u is the temperature in Celcius (C), pH is the acidity, S is the salintiy (‰), D is the depth in meters

The contribution of magnesium sulphate $MgSO_4$ is quantified by

$$\begin{aligned} A_2 &= 21.44 \frac{S}{c} (1 + 0.025T) \\ P_1 &= 1 \\ P_2 &= 1 - 1.37 * 10^{-4} Z + 6.2 * 10^{-9} Z^2 \\ f_2 &= \frac{8.17 * 10^{((8-1990)/(T+273))}}{1 + 0.0018(S - 35)} \end{aligned} \quad \text{Equation (54)}$$

Pure water viscosity contribution for temperature :

$$T \leq 20^\circ C \rightarrow A_3 = 4.937 * 10^{-4} - 2.59 * 10^{-5} T + 9.11 * 10^{-7} T^2 - 1.5 * 10^{-8} T^3 \quad \text{Equation (55)}$$

$$T > 20^\circ C \rightarrow A_3 = 3.964 * 10^{-4} - 1.146 * 10^{-5} T + 1.45 * 10^{-7} T^2 - 6.5 * 10^{-8} T^3$$

$$P_3 = 1 - 3.83 * 10^{-5} Z + 4.9 * 10^{-10} Z^2$$

Francois R. E., Garrison G. R., "Sound absorption based on ocean measurements: Part I: Pure water and magnesium sulfate contributions", Journal of the Acoustical Society of America, 72(3), 896-907, 1982.

Francois R. E., Garrison G. R., "Sound absorption based on ocean measurements: Part II: Boric acid contribution and equation for total absorption", Journal of the Acoustical Society of America, 72(6), 1879-1890, 1982.

APPENDIX E

Table number I and II shows the results for the SSP close to the source simulated by the Xavier ray path propagation (THALES). This simulation is the most accurate to the channel.

Table I .Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth. The SSP used was measured close to the source and the HD was applied from the direction of received to the simulated to avoid the missing point. (True solution: range 9 km ; depth 56 m)

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	15%	9%	25%	18%	24%
56m	19%	15%	15%	12%	12%
62m	24%	25%	21%	24%	22%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	7%	14%	18%	16%	28%
56m	3%	8%	12%	13%	13%
62m	11%	14%	7%	6%	9%

Table II. Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth from the reverse direction, from simulated to the received.

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	19%	25%	22%	11%	12%
56m	13%	29%	33%	12%	5%
62m	15%	22%	29%	15%	26%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	5%	5%	12%	0%	14%
56m	8%	5%	18%	2%	8%
62m	8%	4%	26%	1%	21%

Table number III and IV shows the results for the SSP evaluated by the average between the SSP measured close to the source and the one measured close to the receiver. The simulation was performed by the RAMSEAS (THALES).

Table III .Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth. The SSP used was the mean of the two SSP measured and the HD was applied from the direction of received to the simulated to avoid the missing point. (True solution: range 9 km ; depth 56 m)

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	29%	27%	18%	23%	23%
56m	37%	28%	23%	19%	18%
62m	38%	40%	22%	23%	13%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	8%	6%	18%	13%	25%
56m	5%	13%	12%	15%	55%
62m	13%	15%	9%	11%	14%

Table IV. Percentage of pings detected with maximal error from the true position up to 1 km in range and 10 m in depth from the reverse direction, from simulated to the received.

% detection in range with accepted error up to 1km					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	20%	11%	24%	20%	29%
56m	25%	18%	25%	25%	19%
62m	29%	21%	23%	28%	11%
% detection in depth with accepted error up to 10m					
Depth	MaxHD	MeanHD	MedHD	Part4-HD	Part4HD
52.5m	62%	73%	40%	62%	29%
56m	44%	62%	31%	40%	72%
62m	42%	47%	12%	19%	20%

APPENDIX F

% detection in range with accepted error up to 1km (SSP close to the source X.program) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	27%	3%	13%	23%	7%	3%	2%	5%
	SF-disk 9	0%	1%	2%	14%	31%	96%	73%	100%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	32%	2%	14%	31%	6%	2%	2%	7%
	SF-disk 9	0%	2%	2%	15%	37%	96%	72%	99%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	26%	7%	14%	35%	8%	1%	2%	8%
	SF-disk 9	0%	2%	5%	18%	29%	97%	68%	98%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	34%	5%	21%	37%	6%	2%	1%	15%
	SF-disk 9	0%	3%	5%	19%	27%	88%	67%	94%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	24%	7%	28%	29%	16%	12%	12%	13%
	SF-disk 9	0%	8%	3%	15%	24%	78%	69%	88%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	24%	14%	25%	28%	21%	15%	15%	15%
	SF-disk 9	6%	14%	4%	13%	20%	65%	55%	68%
1 Hydrophone (hydrophone 1)	No S. Filter	24%	25%	21%	22%	24%	28%	26%	23%
	SF-disk 9	21%	28%	9%	12%	21%	44%	42%	47%
% detection in depth with accepted error up to 10m (SSP close to the source X.program)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	9%	38%	22%	29%	31%	36%	38%	49%
	SF-disk 9	0%	0%	0%	13%	0%	0%	0%	0%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	7%	38%	23%	26%	27%	32%	35%	47%
	SF-disk 9	0%	0%	0%	12%	0%	0%	0%	0%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	8%	34%	23%	26%	27%	26%	31%	46%
	SF-disk 9	0%	0%	0%	14%	0%	0%	0%	0%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	11%	29%	20%	25%	26%	24%	27%	43%
	SF-disk 9	0%	0%	0%	16%	0%	0%	0%	0%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	9%	28%	16%	18%	19%	24%	27%	34%
	SF-disk 9	0%	0%	0%	11%	0%	0%	0%	0%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	13%	27%	11%	20%	17%	22%	25%	38%
	SF-disk 9	0%	0%	0%	8%	0%	0%	0%	0%
1 Hydrophone (hydrophone 1)	No S. Filter	11%	14%	7%	9%	6%	15%	15%	22%
	SF-disk 9	0%	0%	0%	0%	0%	0%	0%	0%

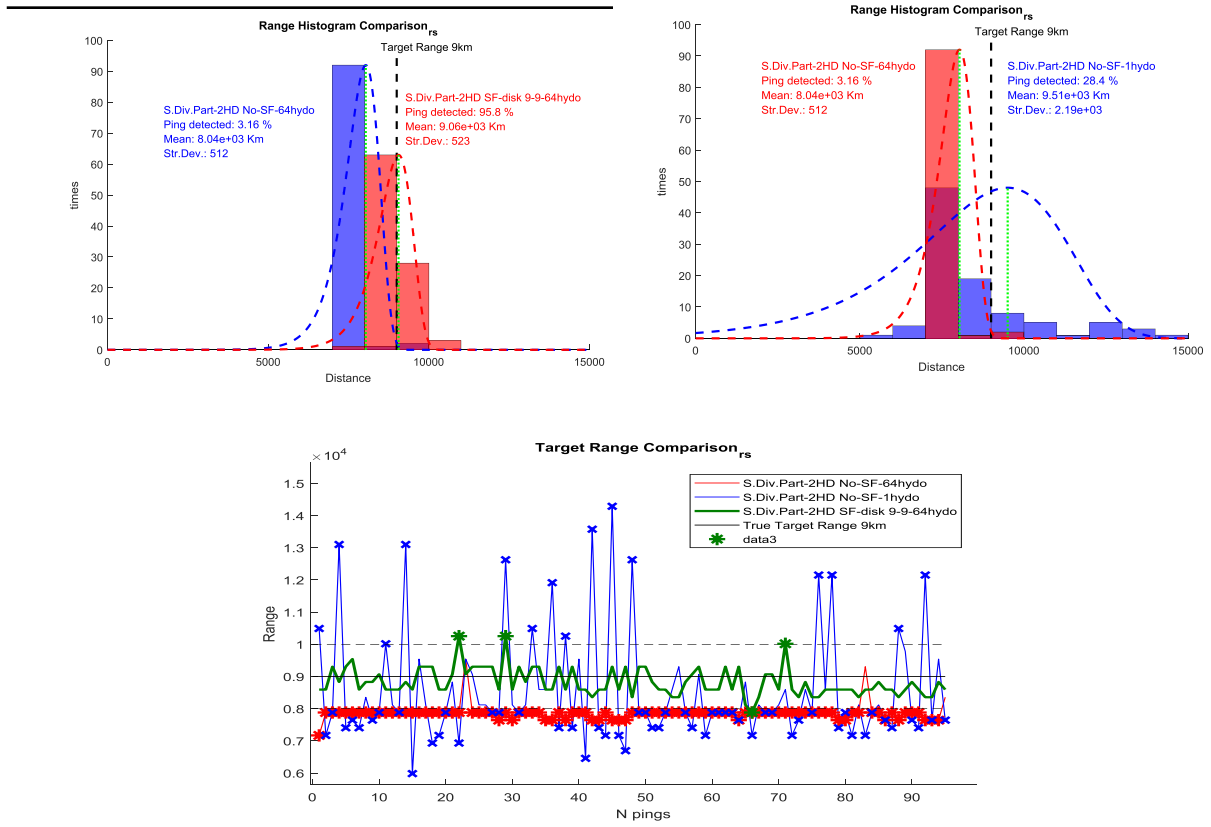


Fig. 87. Histogram of the Partial-1HD applied to range localization (top) and detected range variation compared with true target location.

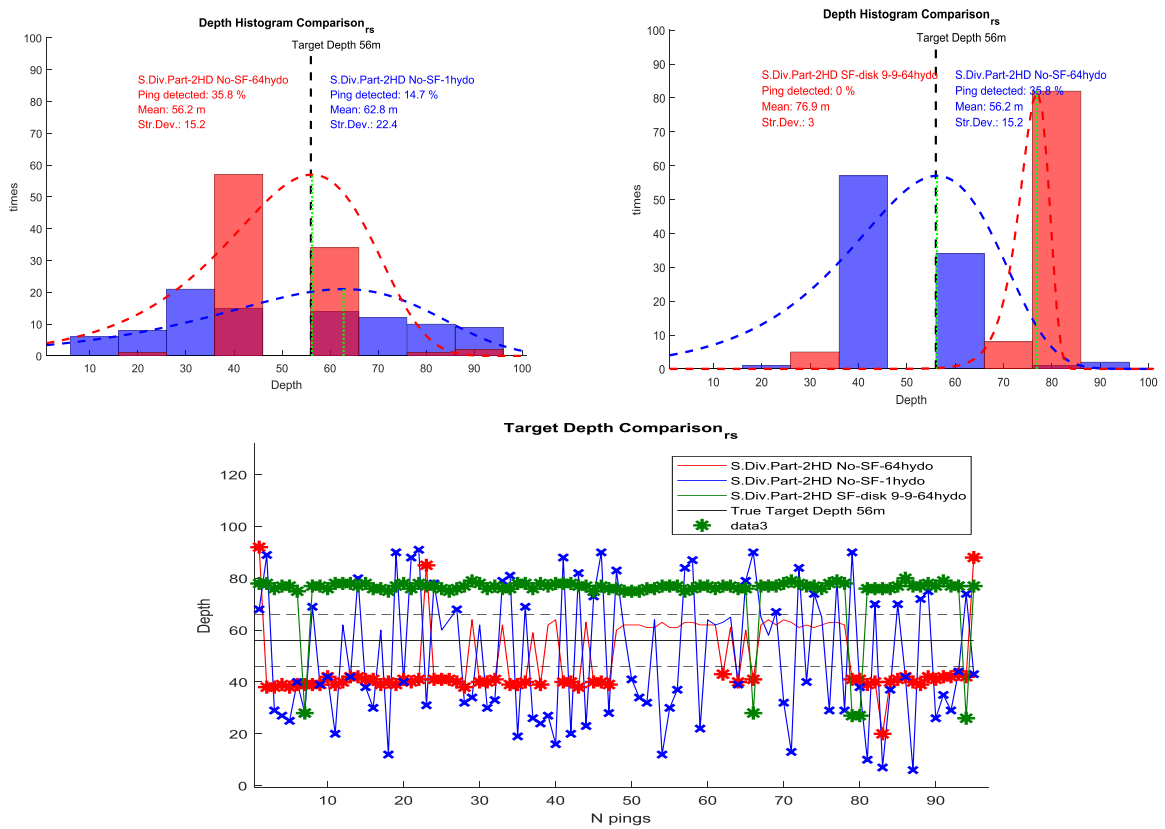


Fig. 88. Histogram of the Partial-1HD applied to range localization (top) and detected range variation compared with true target location.

% detection in range with accepted error up to 1km (SSP Mean) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	69%	49%	43%	46%	46%	46%	48%	71%
	SF-disk 9	77%	85%	17%	51%	45%	87%	99%	66%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	65%	46%	44%	46%	45%	45%	45%	64%
	SF-disk 9	75%	86%	19%	52%	47%	86%	99%	56%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	62%	45%	41%	40%	44%	44%	46%	57%
	SF-disk 9	72%	89%	19%	44%	44%	78%	99%	59%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	64%	43%	39%	43%	41%	44%	45%	53%
	SF-disk 9	67%	80%	14%	44%	41%	67%	91%	45%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	59%	40%	40%	41%	36%	41%	47%	52%
	SF-disk 9	74%	75%	19%	35%	41%	61%	82%	47%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	60%	45%	45%	22%	37%	43%	39%	42%
	SF-disk 9	76%	72%	17%	20%	29%	46%	61%	40%
1 Hydrophone (hydrophone 1)	No S. Filter	38%	40%	22%	13%	23%	29%	37%	27%
	SF-disk 9	58%	48%	14%	5%	19%	22%	37%	26%
% detection in depth with accepted error up to 10m (SSP Mean)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	32%	34%	17%	39%	40%	41%	48%
	SF-disk 9	0%	0%	2%	28%	6%	0%	0%	15%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	35%	34%	16%	39%	39%	40%	55%
	SF-disk 9	0%	0%	2%	31%	5%	2%	0%	21%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	36%	28%	18%	33%	37%	38%	51%
	SF-disk 9	0%	0%	1%	25%	4%	2%	0%	20%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	2%	33%	31%	15%	37%	37%	35%	47%
	SF-disk 9	0%	0%	2%	26%	5%	1%	0%	21%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	8%	24%	27%	23%	22%	34%	38%	43%
	SF-disk 9	0%	0%	1%	32%	2%	2%	1%	16%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	12%	23%	19%	29%	27%	32%	27%	31%
	SF-disk 9	0%	0%	1%	20%	1%	2%	1%	12%
1 Hydrophone (hydrophone 1)	No S. Filter	13%	15%	9%	14%	11%	14%	16%	19%
	SF-disk 9	0%	0%	2%	22%	2%	0%	0%	3%

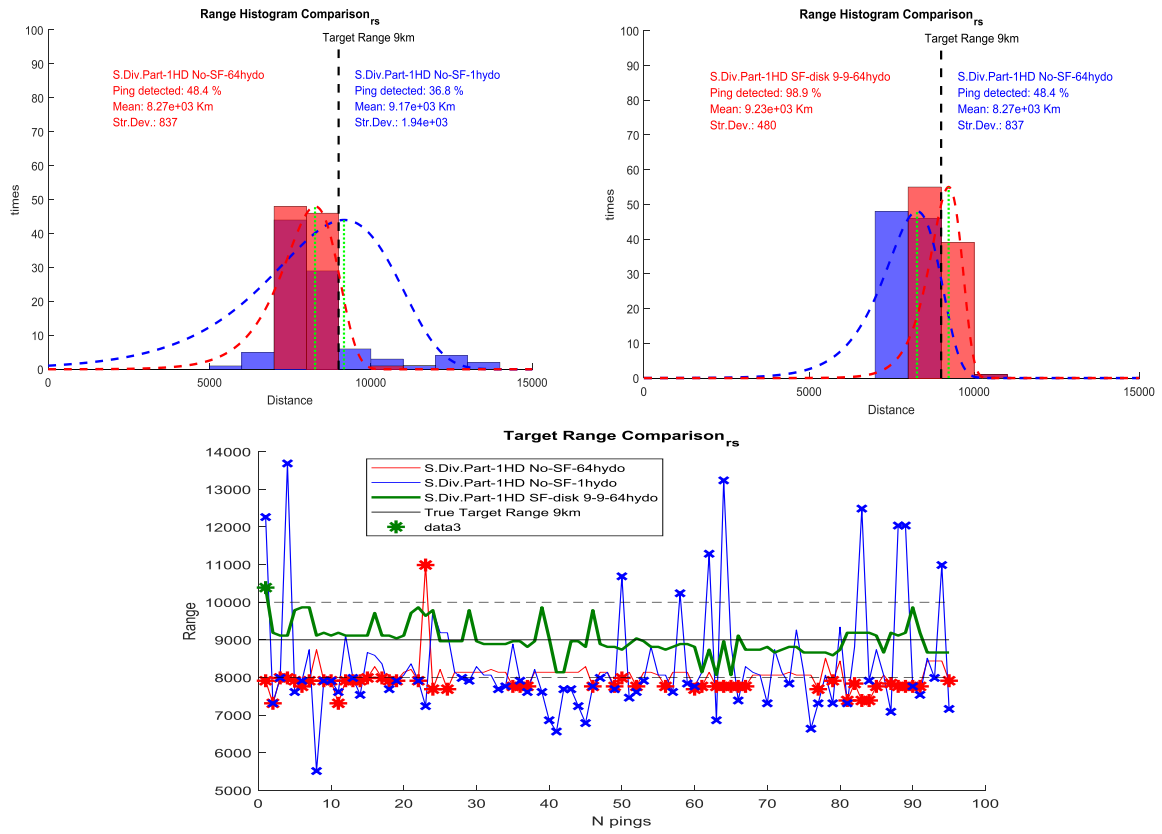


Fig. 89. Histogram of the Partial-1HD applied to range localization (top) and detected range variation compared with true target location.

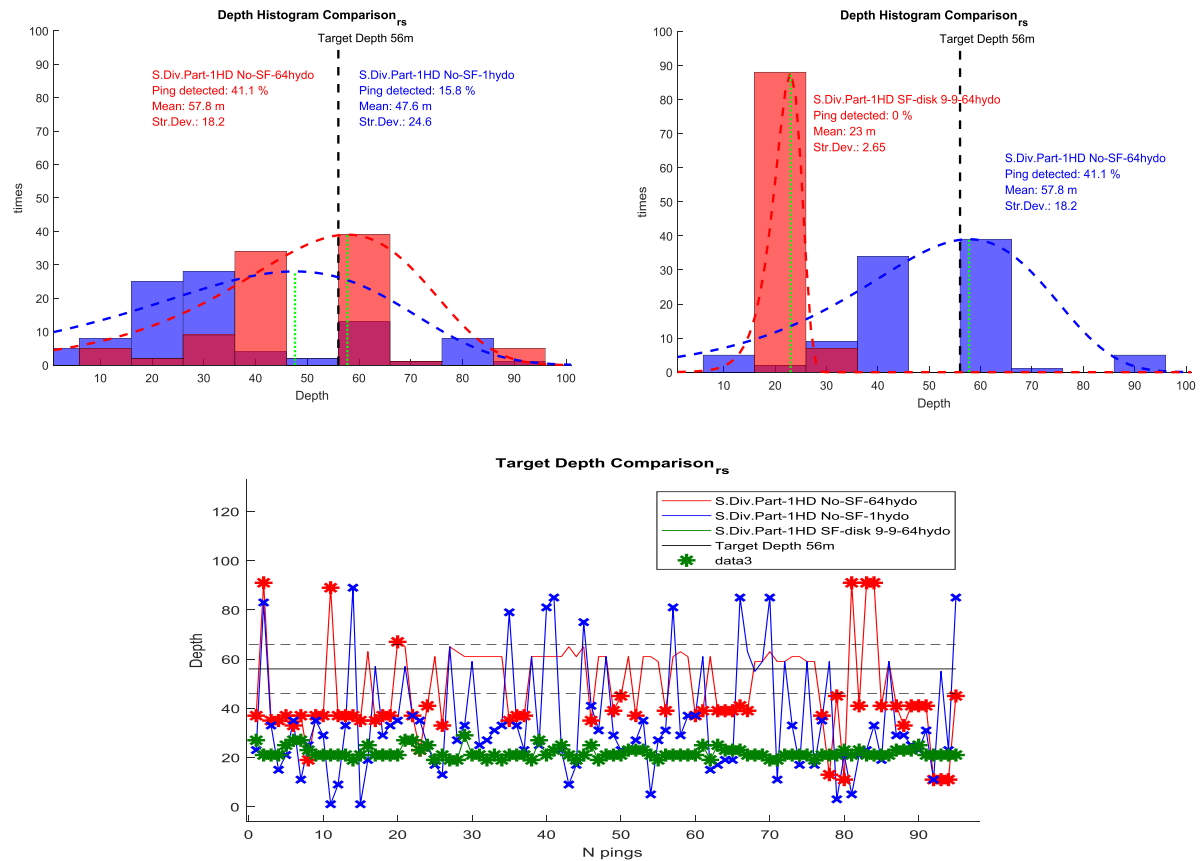


Fig. 90. Histogram of the Partial-1HD applied to range localization (top) and detected range variation compared with true target location.

% detection in range with accepted error up to 1km (SSP close to the source X.program)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
1 Hydrophone (H.index 50)	No S. Filter	15%	19%	19%	29%	13%	13%	22%	20%
	SF-disk 9	9%	20%	13%	24%	25%	47%	49%	20%
Spacing of 1 hydrophone (H.index 1 and 2)	No S. Filter	20%	27%	19%	11%	24%	22%	24%	48%
	SF-disk 9	18%	26%	8%	3%	25%	57%	52%	48%
Spacing of 3 hydrophones (H.index 1 and 4)	No S. Filter	27%	19%	18%	14%	23%	19%	21%	54%
	SF-disk 9	14%	23%	8%	12%	22%	59%	62%	54%
Spacing of 7 hydrophones (H.index 1 and 8)	No S. Filter	25%	23%	24%	22%	23%	22%	35%	49%
	SF-disk 9	9%	23%	12%	4%	20%	62%	54%	49%
Spacing of 15 hydrophones (H.index 1 and 16)	No S. Filter	24%	19%	26%	18%	21%	19%	29%	58%
	SF-disk 9	3%	17%	4%	6%	19%	61%	65%	58%
Spacing of 31 hydrophones (H.index 1 and 32)	No S. Filter	33%	23%	22%	32%	25%	19%	22%	67%
	SF-disk 9	6%	14%	5%	14%	20%	61%	52%	67%

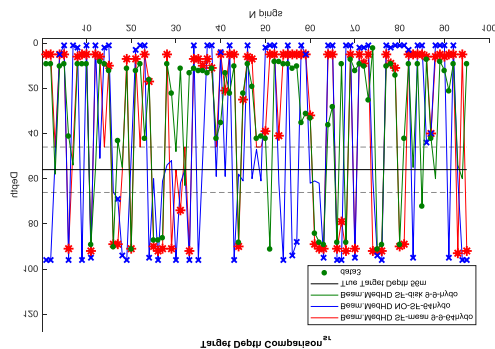
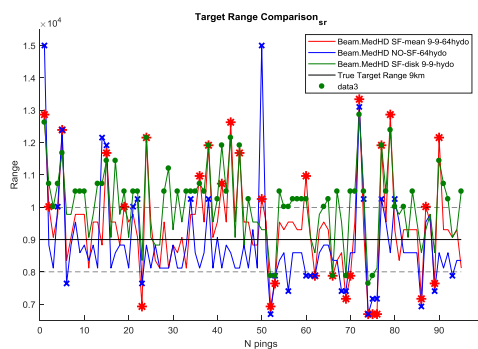
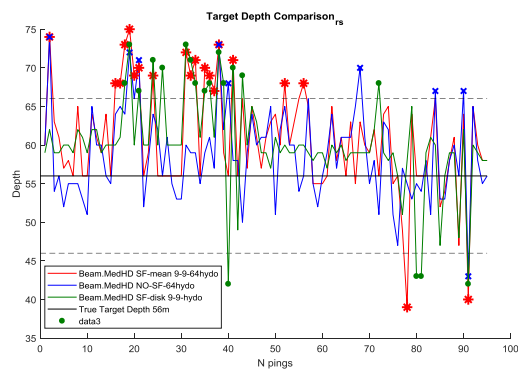
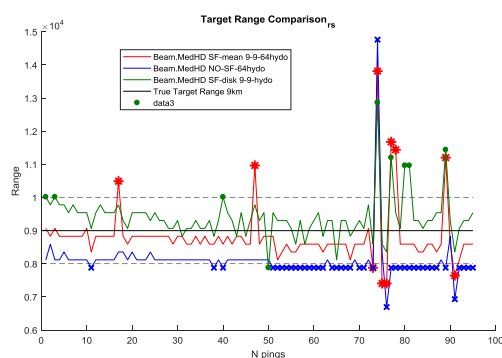
% detection in range with accepted error up to 1km (SSP Mean) HD direction received to simulated (Forward HD)									
		Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD	Prob HD
1 Hydrophone (H.index 50)	No S. Filter	27%	25%	17%	22%	18%	18%	18%	20%
	SF-disk 9	56%	47%	13%	33%	19%	22%	49%	20%
Spacing of 1 hydrophone (H.index 1 and 2)	No S. Filter	45%	43%	28%	12%	35%	38%	34%	48%
	SF-disk 9	68%	59%	12%	4%	14%	31%	62%	48%
Spacing of 3 hydrophones (H.index 1 and 4)	No S. Filter	57%	35%	29%	8%	27%	28%	36%	54%
	SF-disk 9	66%	62%	12%	5%	19%	27%	59%	54%
Spacing of 7 hydrophones (H.index 1 and 8)	No S. Filter	57%	43%	32%	17%	35%	37%	33%	49%
	SF-disk 9	67%	63%	11%	6%	19%	34%	65%	49%
Spacing of 15 hydrophones (H.index 1 and 16)	No S. Filter	55%	43%	25%	20%	33%	43%	34%	58%
	SF-disk 9	72%	69%	7%	14%	18%	32%	67%	58%
Spacing of 31 hydrophones (H.index 1 and 32)	No S. Filter	61%	51%	34%	23%	35%	42%	40%	67%
	SF-disk 9	79%	76%	17%	22%	29%	44%	74%	67%

APPENDIX G

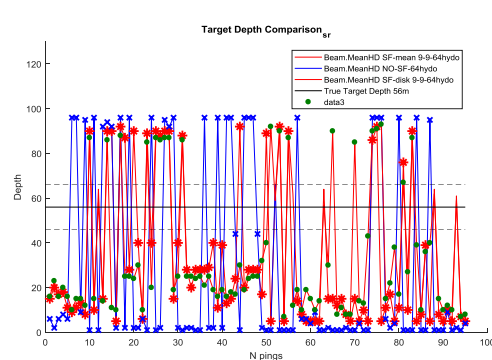
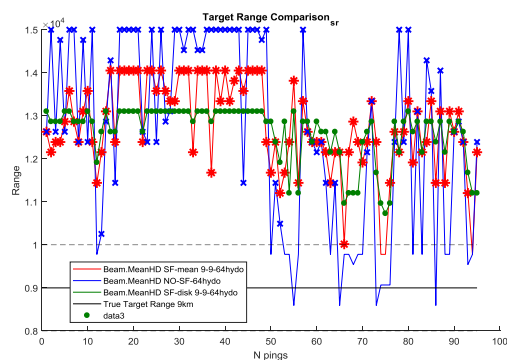
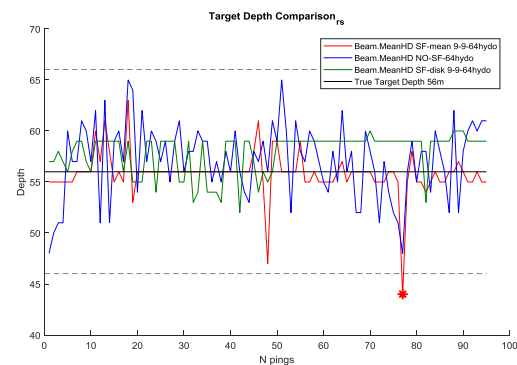
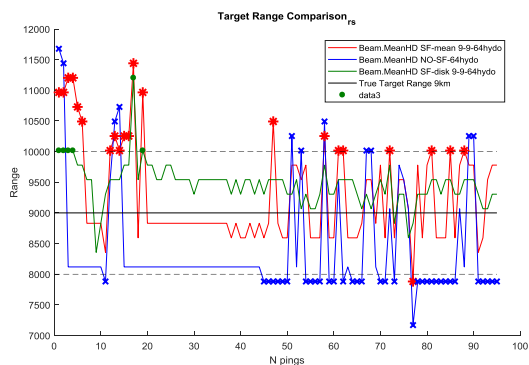
% detection in range with accepted error up to 1km (SSP close to the source X.Program) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	36%	52%	56%	27%	55%	52%	55%
	SF-Mean 9	42%	77%	89%	40%	73%	71%	74%
	SF-Disk 9	54%	94%	91%	44%	81%	84%	85%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	29%	53%	53%	33%	51%	52%	57%
	SF-Mean 9	41%	78%	86%	40%	73%	68%	72%
	SF-Disk 9	54%	95%	92%	41%	82%	80%	85%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	33%	52%	53%	32%	49%	49%	53%
	SF-Mean 9	43%	73%	89%	38%	71%	68%	67%
	SF-Disk 9	57%	91%	91%	39%	80%	82%	81%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	34%	64%	46%	39%	58%	60%	60%
	SF-Mean 9	45%	83%	87%	40%	76%	79%	78%
	SF-Disk 9	67%	98%	93%	42%	91%	95%	97%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	38%	53%	53%	37%	60%	54%	54%
	SF-Mean 9	54%	44%	52%	47%	39%	38%	40%
	SF-Disk 9	67%	69%	44%	56%	54%	57%	63%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	51%	47%	25%	37%	46%	46%	46%
	SF-Mean 9	65%	46%	23%	41%	39%	42%	46%
	SF-Disk 9	73%	63%	21%	48%	46%	55%	59%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	25%	25%	68%	32%	48%	49%	33%
	SF-Mean 9	0%	3%	68%	55%	42%	21%	14%
	SF-Disk 9	0%	0%	36%	40%	14%	1%	0%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	25%	23%	69%	33%	47%	51%	40%
	SF-Mean 9	0%	3%	67%	51%	42%	19%	12%
	SF-Disk 9	0%	0%	36%	37%	13%	1%	1%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	16%	24%	68%	31%	42%	46%	38%
	SF-Mean 9	0%	2%	73%	45%	38%	15%	11%
	SF-Disk 9	0%	0%	31%	39%	12%	2%	1%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	17%	24%	71%	33%	47%	53%	38%
	SF-Mean 9	0%	2%	68%	52%	36%	21%	9%
	SF-Disk 9	0%	0%	24%	43%	5%	1%	1%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	3%	23%	62%	34%	24%	24%	23%
	SF-Mean 9	0%	7%	60%	63%	28%	22%	15%
	SF-Disk 9	0%	1%	19%	53%	8%	1%	0%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	3%	12%	39%	29%	17%	19%	22%
	SF-Mean 9	2%	2%	20%	36%	14%	12%	7%
	SF-Disk 9	0%	0%	11%	40%	6%	4%	2%

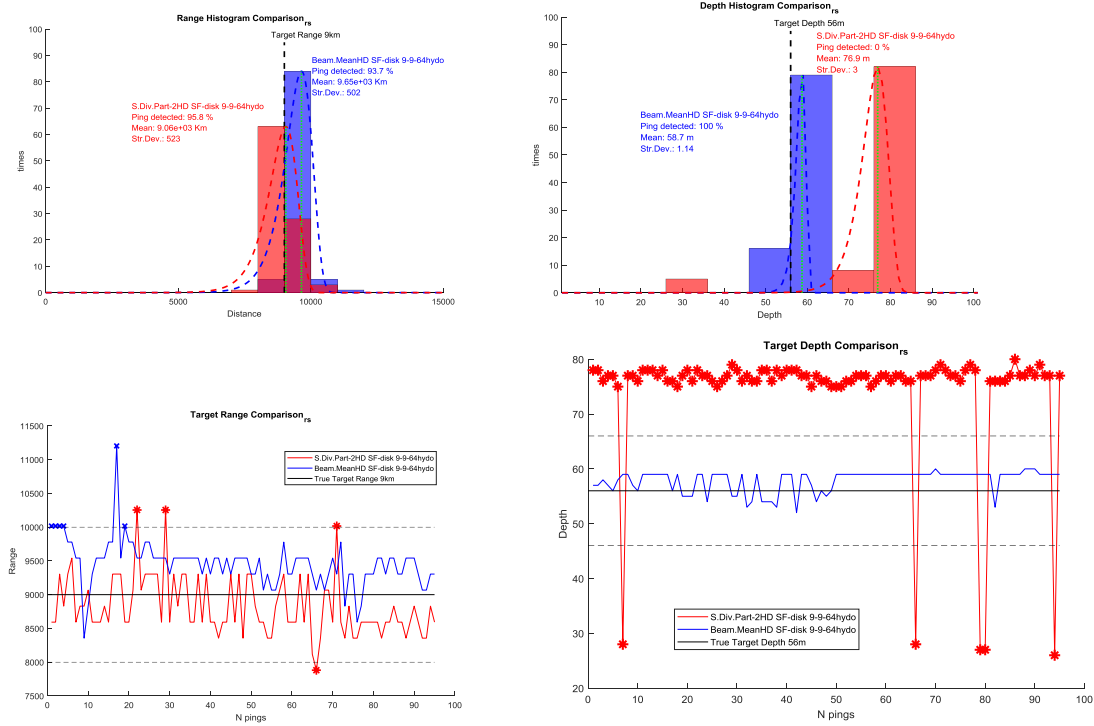
% detection in depth with accepted error up to 10m (SSP close to the source X.Program) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	61%	100%	88%	29%	94%	96%	96%
	SF-Mean 9	81%	99%	76%	21%	95%	97%	100%
	SF-Disk 9	81%	100%	80%	22%	100%	100%	100%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	53%	100%	85%	25%	94%	94%	95%
	SF-Mean 9	79%	99%	66%	22%	95%	98%	98%
	SF-Disk 9	80%	100%	82%	22%	99%	100%	100%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	56%	100%	89%	29%	93%	95%	94%
	SF-Mean 9	79%	99%	73%	22%	95%	98%	98%
	SF-Disk 9	83%	100%	78%	25%	100%	100%	100%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	58%	100%	84%	29%	97%	98%	98%
	SF-Mean 9	81%	100%	66%	19%	97%	100%	100%
	SF-Disk 9	85%	100%	82%	20%	100%	100%	100%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	62%	99%	77%	34%	98%	99%	99%
	SF-Mean 9	81%	98%	91%	31%	99%	98%	99%
	SF-Disk 9	84%	100%	95%	31%	100%	100%	100%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	76%	98%	71%	40%	95%	96%	98%
	SF-Mean 9	92%	99%	87%	29%	100%	100%	98%
	SF-Disk 9	95%	99%	93%	31%	100%	100%	99%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	24%	26%	4%	0%	0%
	SF-Mean 9	5%	6%	11%	36%	9%	4%	5%
	SF-Disk 9	5%	5%	11%	16%	3%	2%	3%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	27%	24%	3%	0%	0%
	SF-Mean 9	5%	4%	15%	36%	2%	3%	3%
	SF-Disk 9	5%	5%	11%	13%	1%	2%	3%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	1%	32%	24%	1%	0%	0%
	SF-Mean 9	5%	2%	16%	32%	4%	3%	4%
	SF-Disk 9	4%	6%	11%	20%	3%	2%	1%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	0%	14%	15%	0%	0%	0%
	SF-Mean 9	3%	7%	3%	31%	2%	1%	3%
	SF-Disk 9	7%	7%	3%	13%	2%	1%	3%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	1%	2%	19%	0%	0%	0%
	SF-Mean 9	4%	6%	4%	24%	4%	2%	5%
	SF-Disk 9	8%	11%	2%	25%	8%	7%	9%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	1%	3%	19%	0%	0%	0%
	SF-Mean 9	2%	4%	4%	23%	3%	4%	3%
	SF-Disk 9	7%	5%	11%	19%	4%	5%	5%

MedHD



MeanHD

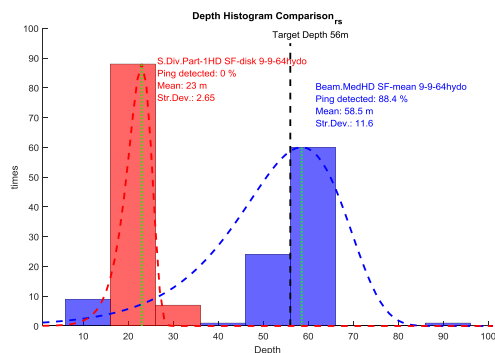
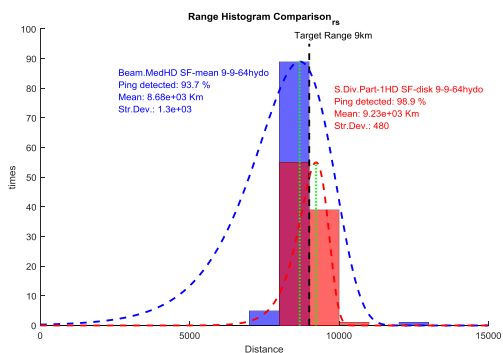
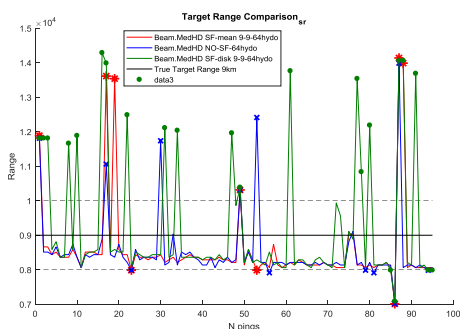
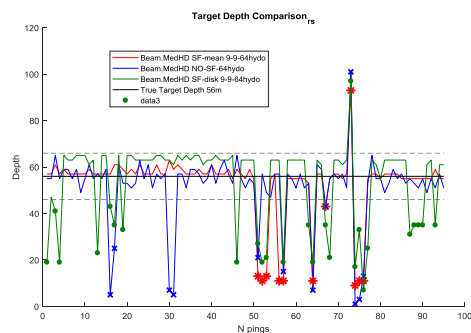
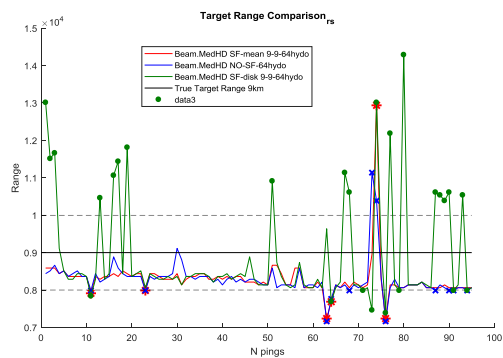


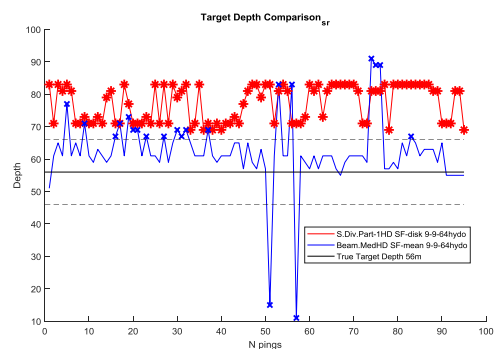
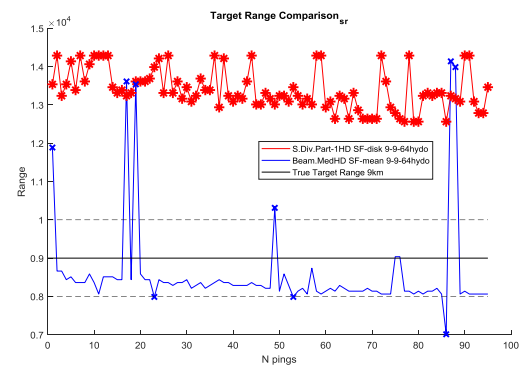
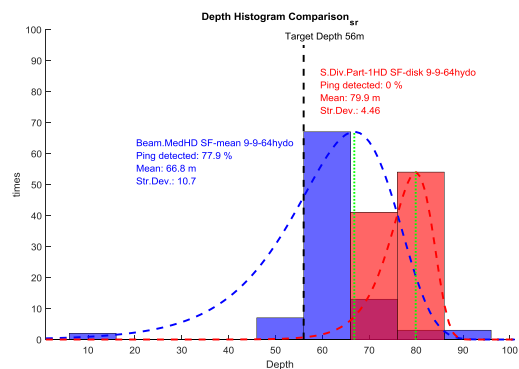
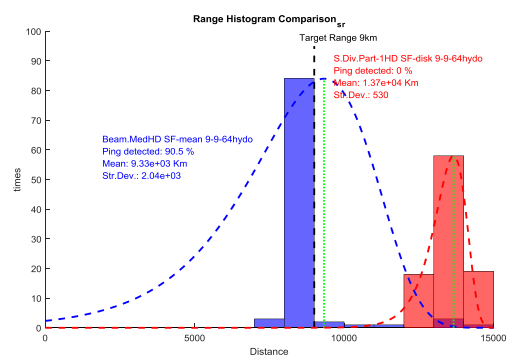
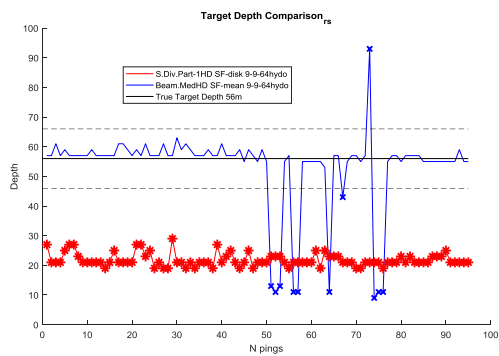
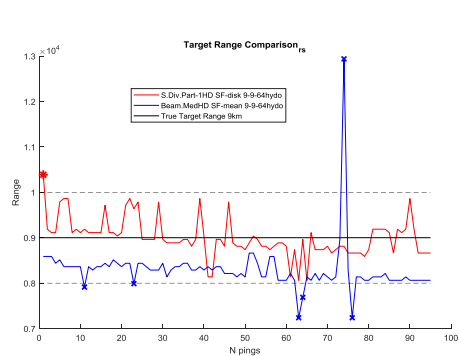


SSP mean

% detection in range with accepted error up to 1km (SSP Mean) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	23%	78%	87%	47%	74%	75%	71%
	SF-Mean 9	31%	72%	94%	52%	68%	67%	66%
	SF-Disk 9	36%	49%	73%	57%	58%	52%	48%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	26%	76%	87%	52%	73%	72%	72%
	SF-Mean 9	33%	69%	89%	47%	69%	65%	64%
	SF-Disk 9	34%	52%	76%	57%	58%	52%	51%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	25%	78%	81%	43%	73%	74%	73%
	SF-Mean 9	34%	73%	85%	41%	67%	67%	65%
	SF-Disk 9	33%	51%	76%	46%	59%	55%	53%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	32%	69%	83%	46%	73%	67%	67%
	SF-Mean 9	33%	71%	82%	58%	71%	67%	67%
	SF-Disk 9	44%	56%	69%	47%	56%	52%	53%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	27%	31%	62%	43%	46%	35%	33%
	SF-Mean 9	21%	26%	52%	45%	29%	28%	29%
	SF-Disk 9	43%	19%	31%	59%	19%	19%	20%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	18%	22%	22%	55%	25%	21%	23%
	SF-Mean 9	40%	22%	18%	56%	23%	21%	21%
	SF-Disk 9	55%	22%	13%	53%	15%	18%	22%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	18%	17%	87%	47%	55%	38%	25%
	SF-Mean 9	1%	13%	91%	49%	52%	26%	17%
	SF-Disk 9	0%	3%	76%	55%	40%	14%	8%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	18%	22%	85%	53%	53%	35%	24%
	SF-Mean 9	1%	15%	84%	45%	47%	33%	17%
	SF-Disk 9	0%	5%	76%	56%	38%	16%	11%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	17%	17%	82%	41%	49%	39%	20%
	SF-Mean 9	1%	13%	83%	45%	52%	32%	17%
	SF-Disk 9	0%	3%	77%	48%	38%	19%	12%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	15%	12%	82%	46%	56%	27%	15%
	SF-Mean 9	8%	17%	76%	60%	45%	26%	21%
	SF-Disk 9	3%	8%	68%	53%	26%	16%	15%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	8%	12%	58%	41%	28%	18%	13%
	SF-Mean 9	4%	8%	47%	44%	19%	17%	15%
	SF-Disk 9	3%	6%	26%	54%	15%	13%	9%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	9%	11%	23%	46%	13%	14%	12%
	SF-Mean 9	13%	12%	15%	45%	12%	11%	11%
	SF-Disk 9	13%	7%	8%	43%	9%	9%	8%

% detection in depth with accepted error up to 10m (SSP Mean) HD direction received to simulated (Forward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	29%	80%	87%	32%	69%	69%	66%
	SF-Mean 9	16%	71%	88%	40%	68%	66%	63%
	SF-Disk 9	16%	49%	73%	38%	52%	44%	44%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	31%	80%	88%	41%	68%	67%	68%
	SF-Mean 9	17%	75%	91%	40%	67%	63%	61%
	SF-Disk 9	12%	54%	77%	42%	48%	44%	44%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	16%	80%	85%	35%	68%	74%	69%
	SF-Mean 9	20%	74%	86%	45%	67%	66%	62%
	SF-Disk 9	13%	47%	77%	40%	54%	48%	47%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	4%	66%	77%	36%	73%	69%	64%
	SF-Mean 9	1%	62%	84%	41%	69%	61%	58%
	SF-Disk 9	0%	36%	66%	44%	46%	42%	39%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	0%	17%	34%	37%	28%	20%	18%
	SF-Mean 9	0%	9%	36%	42%	17%	14%	13%
	SF-Disk 9	0%	4%	23%	37%	9%	6%	4%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	1%	5%	11%	38%	9%	7%	5%
	SF-Mean 9	0%	1%	3%	37%	3%	2%	1%
	SF-Disk 9	0%	0%	2%	37%	2%	1%	1%
HD direction simulated to received (Backward HD)								
		MaxHD	MeanHD	MedHD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
Array 64 Hydrophones (from hydrophone 1 to 64)	No S. Filter	37%	63%	81%	39%	62%	54%	55%
	SF-Mean 9	20%	37%	78%	44%	46%	33%	32%
	SF-Disk 9	2%	1%	48%	44%	17%	4%	3%
Array 32 Hydrophones (from hydrophone 1 to 64)	No S. Filter	42%	55%	79%	39%	61%	60%	54%
	SF-Mean 9	23%	36%	77%	37%	49%	32%	31%
	SF-Disk 9	2%	2%	48%	42%	20%	6%	4%
Array 16 Hydrophones (from hydrophone 1 to 64)	No S. Filter	45%	62%	80%	37%	65%	57%	53%
	SF-Mean 9	25%	34%	78%	41%	46%	33%	31%
	SF-Disk 9	1%	3%	46%	44%	19%	3%	2%
Array 8 Hydrophones (from hydrophone 1 to 64)	No S. Filter	36%	52%	81%	32%	67%	55%	49%
	SF-Mean 9	37%	27%	72%	37%	46%	31%	29%
	SF-Disk 9	7%	7%	39%	41%	14%	7%	6%
Array 4 Hydrophones (from hydrophone 1 to 64)	No S. Filter	51%	74%	74%	33%	62%	66%	61%
	SF-Mean 9	47%	52%	66%	45%	55%	54%	51%
	SF-Disk 9	16%	12%	39%	38%	25%	13%	11%
Array 2 Hydrophones (from hydrophone 1 to 64)	No S. Filter	36%	62%	46%	32%	51%	52%	53%
	SF-Mean 9	37%	53%	43%	40%	47%	47%	47%
	SF-Disk 9	9%	23%	25%	38%	22%	21%	22%





APPENDIX H

% detection in range with accepted error up to 1km (SSP close to the source X.Program)									
HD direction received to simulated (Forward HD)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	46%	55%	68%	40%	52%	55%	56%
		10 Hydrophones	46%	60%	66%	28%	55%	58%	63%
	Spatial diversity SF disk [9 9]	20 Hydrophones	2%	6%	3%	13%	28%	85%	78%
		10 Hydrophones	2%	7%	5%	11%	29%	81%	73%
		4 Hydrophones	2%	12%	3%	14%	25%	72%	61%
		2 Hydrophones	4%	11%	5%	12%	25%	61%	54%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	63%	54%	57%	26%	42%	45%	63%
		10 Hydrophones	62%	48%	61%	28%	40%	48%	62%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	5%	11%	12%	34%	95%	60%
		10 Hydrophones	0%	9%	11%	11%	37%	92%	62%
		4 Hydrophones	0%	9%	6%	11%	34%	79%	59%
		2 Hydrophones	7%	18%	17%	13%	37%	53%	51%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	68%	78%	61%	26%	56%	66%	68%
		10 Hydrophones	69%	80%	61%	25%	57%	63%	69%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	2%	5%	12%	56%	86%	47%
		10 Hydrophones	0%	5%	5%	8%	49%	82%	46%
		4 Hydrophones	0%	7%	7%	8%	54%	78%	41%
		2 Hydrophones	1%	12%	8%	17%	39%	65%	41%
% detection in depth with accepted error up to 10m (SSP close to the source X.Program)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	60%	82%	69%	12%	81%	82%	86%
		10 Hydrophones	65%	86%	68%	5%	82%	86%	85%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	0%	11%	0%	0%	0%
		10 Hydrophones	0%	0%	0%	7%	0%	0%	0%
		4 Hydrophones	0%	0%	0%	6%	0%	0%	0%
		2 Hydrophones	0%	0%	0%	3%	0%	0%	0%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	60%	91%	73%	5%	85%	85%	88%
		10 Hydrophones	58%	93%	73%	9%	84%	88%	91%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	0%	20%	0%	0%	0%
		10 Hydrophones	0%	0%	0%	19%	0%	0%	0%
		4 Hydrophones	0%	0%	0%	14%	0%	0%	0%
		2 Hydrophones	0%	0%	0%	11%	0%	0%	0%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	66%	95%	84%	5%	97%	97%	98%
		10 Hydrophones	65%	97%	88%	3%	99%	98%	98%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	0%	22%	0%	0%	0%
		10 Hydrophones	0%	0%	0%	21%	0%	0%	0%
		4 Hydrophones	0%	0%	0%	21%	0%	0%	0%
		2 Hydrophones	0%	0%	0%	25%	0%	0%	0%

% detection in range with accepted error up to 1km (SSP Mean)									
HD direction received to simulated (Forward HD)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	27%	38%	67%	45%	51%	44%	43%
		10 Hydrophones	26%	43%	67%	46%	53%	47%	45%
	Spatial diversity SF disk [9 9]	20 Hydrophones	67%	75%	13%	20%	32%	56%	77%
		10 Hydrophones	64%	76%	12%	18%	28%	55%	79%
		4 Hydrophones	72%	72%	6%	17%	21%	46%	71%
		2 Hydrophones	66%	74%	12%	12%	16%	32%	57%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	39%	31%	64%	34%	37%	29%	29%
		10 Hydrophones	34%	34%	65%	36%	35%	35%	35%
	Spatial diversity SF disk [9 9]	20 Hydrophones	71%	77%	11%	22%	32%	63%	80%
		10 Hydrophones	71%	73%	11%	20%	32%	59%	77%
		4 Hydrophones	78%	74%	9%	17%	24%	54%	71%
		2 Hydrophones	74%	68%	8%	16%	19%	40%	49%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	41%	36%	63%	53%	39%	35%	33%
		10 Hydrophones	39%	38%	58%	51%	37%	38%	37%
	Spatial diversity SF disk [9 9]	20 Hydrophones	77%	93%	77%	18%	83%	97%	98%
		10 Hydrophones	72%	95%	74%	24%	79%	94%	99%
		4 Hydrophones	79%	92%	63%	26%	76%	86%	89%
		2 Hydrophones	79%	91%	55%	23%	66%	82%	91%
% detection in depth with accepted error up to 10m (SSP Mean)									
Array section	Technique	N° of hydrophones equally spaced	Max HD	Mean HD	Med HD	Partial 4HD	Partial 4-HD	Partial 2-HD	Partial 1-HD
1° Array section (hydrophone 1 to 20)	Beamforming SF mean [9 9]	20 Hydrophones	3%	40%	76%	27%	53%	47%	45%
		10 Hydrophones	2%	41%	77%	26%	55%	49%	44%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	1%	29%	1%	1%	0%
		10 Hydrophones	0%	0%	1%	26%	2%	2%	0%
		4 Hydrophones	0%	0%	1%	34%	2%	1%	1%
		2 Hydrophones	0%	0%	0%	35%	0%	1%	0%
2° Array section (hydrophone 21 to 40)	Beamforming SF mean [9 9]	20 Hydrophones	4%	27%	74%	35%	39%	33%	29%
		10 Hydrophones	3%	32%	73%	29%	42%	38%	37%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	1%	33%	1%	0%	0%
		10 Hydrophones	0%	0%	1%	34%	1%	0%	0%
		4 Hydrophones	0%	0%	0%	37%	0%	0%	0%
		2 Hydrophones	0%	0%	0%	47%	0%	0%	0%
3° Array section (hydrophone 41 to 60)	Beamforming SF mean [9 9]	20 Hydrophones	3%	28%	77%	33%	40%	35%	32%
		10 Hydrophones	2%	26%	77%	31%	37%	35%	31%
	Spatial diversity SF disk [9 9]	20 Hydrophones	0%	0%	0%	37%	0%	0%	0%
		10 Hydrophones	0%	0%	0%	41%	0%	0%	0%
		4 Hydrophones	0%	0%	0%	41%	0%	0%	0%
		2 Hydrophones	0%	0%	2%	38%	0%	0%	0%

Résumé étendu

Résumé - Cette thèse porte sur la localisation de sources acoustiques sous-marines avec application à une expérience en mer. Nous proposons une nouvelle méthode d'appariement basée sur une métrique appelée distance de Hausdorff (HD) en tant que fonction de coût à minimiser, afin d'effectuer l'inversion de localisation. La localisation 2D, en distance et en profondeur, est réalisée en faisant correspondre les schémas de différence de temps d'arrivée (TDOA) en utilisant un seul hydrophone à la réception et en faisant correspondre le TDOA et l'Angle d'arrivée (AOA) lors de l'utilisation d'un tableau des hydrophones à la réception, entre des séquences respectivement mesurées et modélisées. Le TDOA modélisé a été obtenu sur la base du modèle de propagation acoustique Ray-path. Les ensembles de données analysés ici ont été collectés dans un contexte de localisation passive en considérant une cible immobile et dans deux expériences : la cuve acoustique de GIPSA-LAB utilisant des systèmes coopératifs et non coopératifs vérifiés par des simulations du rapport signal sur bruit et sur la campagne ALMA 2015, collectée par la Direction générale de l'armement (DGA) en utilisant un système coopératif qui s'est déroulé dans un environnement en eaux peu profondes de la côte sud de la France. Au cours de l'expérience ALMA, les données acoustiques ont été mesurées sur un réseau linéaire vertical (VLA) de 10 m de haut, composé de 64 hydrophones, ce qui permet non seulement d'adapter le TDOA mais également l'angle d'arrivée (AOA). Plusieurs variantes de la distance de Hausdorff sont appliquées dans deux processus différents: premièrement, séparément dans chaque hydrophone, puis combinées pour améliorer la précision de la localisation (diversité spatiale), et la seconde où les informations des différents hydrophones sont combinées (formation de faisceaux), pour trouver l'emplacement cible. Les résultats des deux processus sont comparés et prouvés pour réduire l'ambiguïté soit la profondeur et la portée, améliorant ainsi la précision finale. Le Cramer Rao Bound montrant la variance minimale effectuée sur la base d'équations déterministes est présenté avec le meilleur résultat de chaque processus. Une performance et une précision très satisfaisantes sont obtenues. Les conclusions et les perspectives de ce travail sont discutées à la fin.

Abstract — This thesis addresses an acoustic underwater source localization with application to an at-sea experiment. We propose a new matching method based on a fit-metric called as Hausdorff distance (HD) as a cost-function to be minimized, in order to perform the localization inversion. The 2-D localization, in range and depth, is performed by matching the patterns of time difference of arrival (TDOA) when using only one hydrophone at the reception and by matching the TDOA and the Angle of Arrival (AOA) when using an array of hydrophones at the reception, between respectively measured and modeled sequences. The modelled TDOA was obtained based on the Ray-path acoustic propagation model. The data sets analyzed here were collected during two experiments in a context of passive localization considering a motionless target: The tank of GIPSA-LAB using cooperative and non-cooperative systems which were verified by simulations with respect to the signal-to-noise ratio and the ALMA 2015, collected by the Direction générale de l'armement (DGA) using a cooperative system which took place in a shallow water environment of the southern coast of France. During the ALMA experiment the acoustic data were measured over a 10m-high vertical linear array (VLA), composed of 64 hydrophones, allowing not only matching the TDOA but also the Angle of Arrival (AOA). Several variants of the Hausdorff Distance are applied in two different processes: First, separately in each single hydrophone, and then combined in order to improve the localization accuracy (spatial diversity), and the second, the information from the different hydrophones are combined (beamforming) and the HD variants are applied to find the target location. The results of both processes are compared and proved to reduce the ambiguity either is depth and in range, thus improving the final accuracy. The Cramer Rao Bound showing the minimal variance performed based on deterministic equations is presented with the best result of each process. Very satisfactory performance and accuracy are obtained. The conclusions and perspectives of this work are discussed at the end.