22nd IMEKO TC4 International Symposium & 20th International Workshop on ADC Modelling and Testing
SUPPORTING WORLD DEVELOPMENT THROUGH ELECTRICAL&ELECTRONIC MEASUREMENTS
IASI, ROMANIA, September 14-15, 2017

Accuracy and precision studies for range-only underwater target tracking in shallow waters

I. Masmitja[1], P. J. Bouvet[2], S. Gomariz[1], J. Aguzzi[3], J. del Rio[1], D. Mihai Toma[1]

[1] SARTI Research Group. Electronics Department, Universitat Politècnica de Catalunya. Vilanova i la Geltrú, Spain. Email: ivan.masmitja@upc.edu
[2] Underwater Acoustics Lab, ISEN Brest. C.S. 42807, 29228 Brest cedex 2, France. Email: pierre-jean.bouvet@isen-bretagne.fr
[3] Marine Science Institute (ICM). Consejo Superior de Investigaciones Científica (CSIC). Barcelona, Spain

***Abstract* – This paper studies the precision, and the accuracy, of an underwater target tracking system, using range-only and single-beacon methods, in shallow waters environments. For this study, different field tests have been realized in the OBSEA test site, a well-known and monitored area at 4 km from the coast and at 20 meters of depth, in the Mediterranean Sea (Barcelona). The tests have been conducted using two acoustic underwater modems from the company LinkQuest Inc. Moreover, the autonomous underwater vehicle developed by the *Universitat Politècnica de Catalunya* (called Guanay II) have also used to perform the tests.**

Keywords – Range-only, single-beacon, underwater target tracking, position accuracy, position precision, autonomous vehicle, and AUV.

I. INTRODUCTION

Range-only and single-beacon architecture for underwater target tracking using autonomous vehicles has numerous advantages, such as low deployment complexity, and the possibility to cover large areas. On the other hand, this method can also be integrated in multi-vehicle collaborations, which opens new possibilities for ocean exploration. For these reasons different studies have been conducted during the last years [1].

However, due the complexity of the underwater channel communications, and the complexity to have a standard underwater positioning system, different aspects of this method are still open. For example, the precision and accuracy that can be achieved in shallow waters, which can also be altered for the specific bathymetry of the area.

Previous works that we have conducted recently, [2] and [3], have shown that the specific shallow water environment can cause an important impact in the range error, and therefore, in the accuracy and precision of target localization. As it is well known, the main issue to take into account in shallow waters is the multi-path effect, which can cause important errors in range measurements.

The ranges between two points are usually measured using two acoustic modems. One installed in the target and another one in the vehicle. Typically, these modems have a standard command to know the distances between them using a two-way message exchange. Where the range can be derived easily knowing the Time of Flight (TOF) of the message and the sound velocity in water (approximately 1500 m/s).

However, the exact sound velocity is usually difficult to know, due its sensitivity in front of temperature or salinity variations. This can cause a systematic error in range measurements, and therefore, reduce the accuracy of the target estimation. Moreover, some outliers in range measurements can also be produced through the multipath effect, which introduce a non-Gaussian error in range measurements.

The aim of this paper is to study and characterize the best accuracy and precision that can be reached in shallow water scenarios, using range-only and single-beacon target tracking algorithms. For this propose, different tests have been conducted, and different algorithms have been compered such as, Least Square (LS), Extended Kalman Filter (EKF) and Particle Filters (PF).

In this paper, the definitions of accuracy and precision from the Joint Committee for Guides in Metrology (JCGM) [4] have used, where the accuracy is defined as the closeness of agreement between a measured quantity value and a true quantity value, and the precision as the closeness of agreement between measured quantity values obtained by replicate measurements.

II. RELATED RESULTS IN THE LITERATURE

The complexity of the water channel is well known [5], which introduces different sources of errors in acoustic positioning systems. The main sources of error were explained in our previous work [3].

The multipath effect is the most important one in shallow water environments [6-7], as it was also observed in [3], which can introduce a non-Gaussian noise error and different outlier points [8]. These problems have an important implication in the accuracy and precision of target positioning, especially when the range-only single-beacon method is used.

In this paper, we want to study these issues in our specific scenario, the OBSEA test site in Barcelona, with the main goal of localize and track and underwater target using an Autonomous Underwater Vehicle (AUV), and range-only and single-beacon techniques.

III. DESCRIPTION OF THE METHOD

The main architecture behind the range-only and single-beacon underwater target tracking using autonomous vehicles is shown in Fig. 1. The idea is to estimate the position of an underwater target with a known depth, using only the ranges between the target and an autonomous vehicle, which is in a known position. The autonomous vehicle can be a surface vehicle with a GPS, or an underwater vehicle with a good dead-reckoning system. In our study, the vehicle tested is an AUV used as a surface unmanned vehicle, which has developed by *Universitat Politècnica de Catalunya* (UPC), and it is called Guanay II [9]. This vehicle is equipped with a GPS, and an acoustic modem configured as a master.

On the other hand, the underwater target is a second modem, deployed on the water at 5 meters of depth using a buoy, with GPS position. This modem is used as a slave.

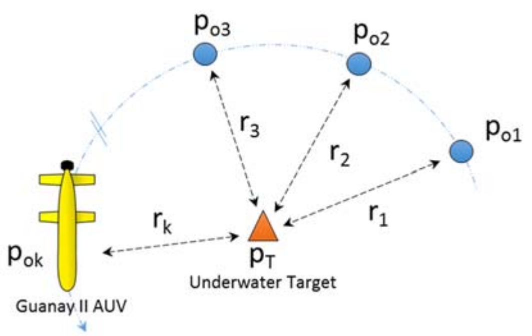

Fig. 1. Representation of the Guanay II (as observer) and the underwater Target

With this configuration, and using the LS, EKF and PF algorithms, a comparative study have been done. These three algorithms are well known and in this paper only the main aspects are presented. If a detailed information is needed, please see the work done in [10-12], and the references therein.

A. Least Square algorithm (LS)

The LS algorithm was used in our previous work [2], where this algorithm was developed to compute the location of a static underwater target using only the range measurements

$$\bar{r}_k = \|\boldsymbol{p}_T - \boldsymbol{p}_{ok}\| + w_k, \quad k \in \{1,2,\dots,m\} \tag{1}$$

where $\boldsymbol{p}_T = [\, x_T \;\; y_T]$ and $\boldsymbol{p}_{ok} = [\, x_{ok} \;\; y_{ok}]$ are the target and the AUV positions at time step k, with some zero mean Gaussian measurement error $w_k \sim \mathcal{N}(0, \sigma^2)$, where σ^2 is its variance.

The main idea of this method is to linearize the system using the squared range measurements. Then, the target position can be computed using different AUV positions, and triangulation techniques.

B. Extended Kalman Filter (EKF)

The EKF algorithm is used to estimate the state vector of a wide variety of non-liner problems. For underwater target tracking using range-only methods, the EKF main parameters are shown below. Firstly, we have the state vector

$$\mathbf{x}_k = [x_{Tk} \; \dot{x}_{Tk} \; y_{Tk} \; \dot{y}_{Tk}]^T \tag{2}$$

where x_{Tk} and y_{Tk} are the target position, and $\dot{x}_{Tk}$ and $\dot{y}_{Tk}$ are their velocities, at time step k. Then, we have the motion model

$$\mathbf{x}_k = \mathbf{F}_{k-1}\,\mathbf{x}_{k-1} + \mathbf{Q}_{k-1} \tag{3}$$

where $\mathbf{F}$ is the state transition matrix, and $\mathbf{Q}$ is the process noise. And finally, the measurement model

$$h(\mathbf{x}_k) = \sqrt{(x_{Tk} - x_{ok})^2 + (y_{Tk} - y_{ok})^2} + w_k \tag{4}$$

where x_{ok} and y_{ok} are the AUV (as an observer) positions at each time step k.

C. Particle Filter (PF)

The main idea behind PF is the use of grids to represent the spatial state, and a posterior computation over these grids recursively. This method has the capability of solving nonlinear estimation problems with a multimodal posterior probability distribution function.

The PF uses the same state vector, motion and measurement models of the EKF to represent each particle of the filter. Moreover, each particle has an associated importance weight

$$W_k^n = p(z_k|\hat{\mathbf{x}}_k^n) \tag{5}$$

which is related to the measurement z_k. And a resampling step which generate a set of new particles from the previous set, according to the importance weights calculated.

D. Test Setup

A field tests have conducted in the underwater observatory OBSEA [13], in Barcelona, to observe the filters' performance. This observatory is at 4 km from the coast, and in a shallow water environment (20 meters of depth).

Although the algorithms explained above had designed for tracking a moving target, a preliminary test have done to observe its performance in a static scenario, which can be observed as an initialization point for the dynamic scenario. Therefore, this is an important point to study, which will have an important effect, not only for static targets, but also for moving targets. The test conducted in the OBSEA to study this performance was designed as follows.

One linkQuest Inc. modem was deployed using the OBSEA's buoy, which was attached at 5 meters of depth, and a second modem was installed in the Guanay II AUV, Fig. 2. The first modem was used as a slave, which only responded the synchronization commands sent by the master modem, the AUV modem.

The path designed for this test was two pentagon lines around the target, which had 100 meters and 200 meters of radius, Fig. 2. During this path, the AUV was constantly measuring the ranges between the target and himself, with a period of 30 seconds, approximately. The pentagon shape was used because, whereas a circle trajectory is faster to break the system's ambiguity, the AUV's navigation system is not optimized to do that kind of trajectories, and the pentagon shape is close enough to a circle shape.

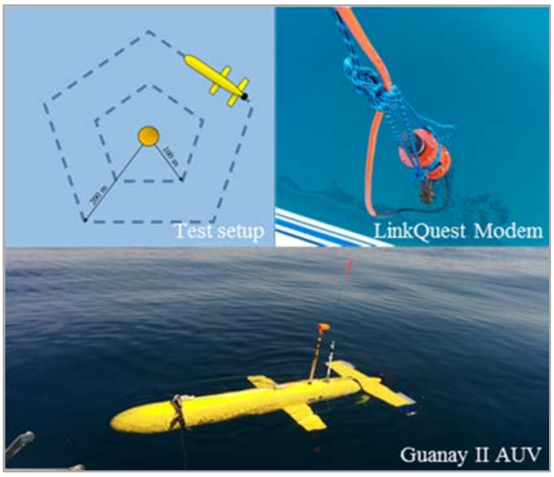

Fig. 2. Upper left: test setup with target position (orange circle), and Guanay II trajectories, pentagons with 100 m and 200 m of radius. Upper right: picture of one of the LinkQuest Inc. acoustic modems used for the test. Lower picture: Guanay II during the mission.

IV. RESULTS AND DISCUSSIONS

The path done by our AUV during the test can be observed in Fig. 3, where the big blue circles are the waypoints (WP) of the path, the small blue circles are the true path completed and also indicates when the AUV obtained a new range, and the red triangle is the true target position. Moreover, the black start and circle indicate the start point, and the end point, respectively.

We can see that Guanay II started at 50 meters from the target and then it did a first pentagon, then went to the centre and started the second and biggest pentagon. During all this path, it took 83 ranges between himself and the target position.

Different simulations have performed, using the same GPS positions that Guanay II acquired during the test, but with an ideal group of ranges instead of the acquired ones. This allow to simulate different scenarios with different noise levels to study the performance of the algorithms.

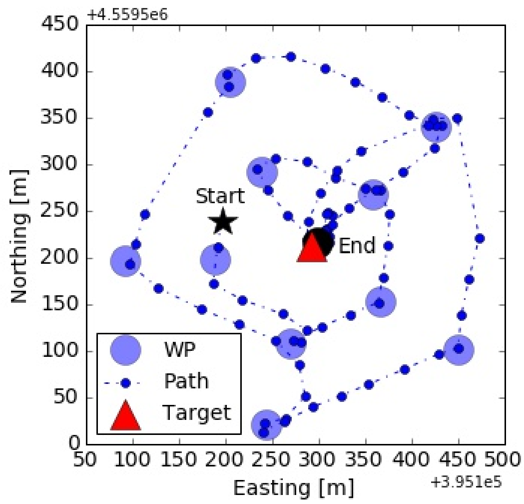

Fig. 3. Guanay II trajectory during the field test (blue dots). Moreover, we can observe the initial and final position (black start and dot respectively), the waypoints which indicated the path (big blue dots), and, finally, the true target position (red triangle).

A. Simulations with true GPS positions

To study de boundaries of the three algorithms (LS, EKF and PF), we have run them under three different circumstances, a small-noise scenario (a Gaussian noise with a Standard Deviation (STD) equal to 1 meters), a medium-noise scenario (with a STD equal to 2 meters), and a high-noise scenario (with a STD equal to 4 meters).

As an example, we have taken the medium-noise scenario, and we have run it 100 times to observe the filters response variability, and the Root Mean Square Error (RMSE) as a function of time, or what is the same, as a function of each new range introduced in the filters. This can be observed on Fig. 4, where we can see the mean of the RMSE after 100 iterations (dark line) and its standard deviation (light coloured areas). The setting time T_s is computed when the error is below the dotted line configured at 20 m.

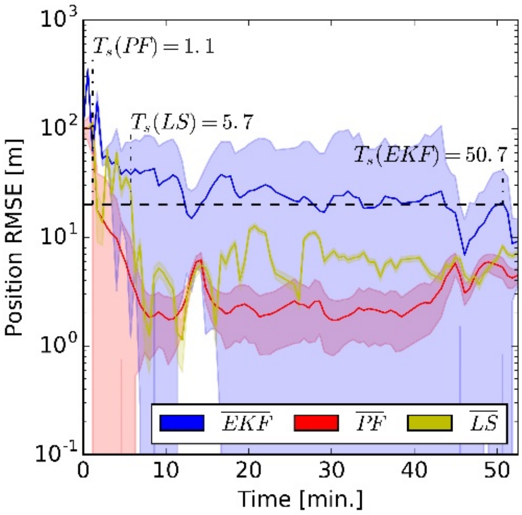

Fig. 4. Target position error versus time, or new range. Dark line is the mean after 100 iterations, and light coloured area is its STD. For a Gaussian noise of 0m of mean and 2 m of STD.

We can observe that the EKF have the worst performance, which means that it is very sensitive with the noise, and therefore it have difficulties to estimate the true target position. It was not until the end of the simulation that it can compute the target position with an error less than 20 meters. Specifically, after 50.7 minutes, which is too much for target tracking purposes. On the other hand, both PF and LS algorithms had much better performance, which had a setting time of 1.1 and 5.7 minutes, respectively.

Finally, on Fig. 5 a better representation of the algorithms' accuracy and precision are shown, where each scenario have been iterated 100 times. The graphs show the last 10 filters' estimations for each iteration, in total 1000 points (small dots). Moreover, the ellipses show the covariance matrix of each dataset in two dimensions. This covariance represents de 2D standard deviation of the estimations with a 95.45% of confidence interval. The main points to remark on Fig. 5 are:

Least Square algorithm (LS): we can see that the LS algorithm have the lowest noise influence, which have a high precision, however its accuracy is not as good as its precision. It have a STD of 0.26 m and 1.42 m, on their axis, and a bias error of 5.94 m (for 1 m of noise).

Particle Filter (PF): the PF have a quite good performance in low and medium noisy scenarios, which have a high precision, and higher accuracy than LS. It have a STD of 0.85 m and 1.61 m, on their axis, and a bias error of 4.68 m (for 1 m of noise). This indicate its robustness in front of range noise. However in higher levels of noise its prediction becomes worst

Extended Kalman Filter (EKF): on the other hand, this algorithm is the most vulnerable in front of range noise, as observed also previously. Whereas its precision is really poor, it have a good accuracy. It have a STD of 4.95 m and 7.65 m, on their axis, and a bias error of 0.83 m (for 1 m of noise).

All these parameters are summarised in Table 1.

B. Comparison between simulations and field test

After the simulations explained above, the ranges' noise have studied to obtain its value and shape. With this information, the simulation results, and the real result obtained during the test, can be compered. This allow us to validate the mathematical formulation, and the algorithms.

The ranges error obtained during the test is shown on Fig. 6. Moreover, its histogram can be observed on Fig. 7, where we can see that the error has a Gaussian shape distribution with -0.22 m of mean and 2.59 m of Standard Deviation (STD).

Finally, the target position estimations obtained during the OBSEA test are shown on Fig. 8, where it is represented the last 10 estimations of the filters. Whit these points have also computed its covariance, as have done before (elliptic lines). This result can be compared with the simulation results to see its correlation.

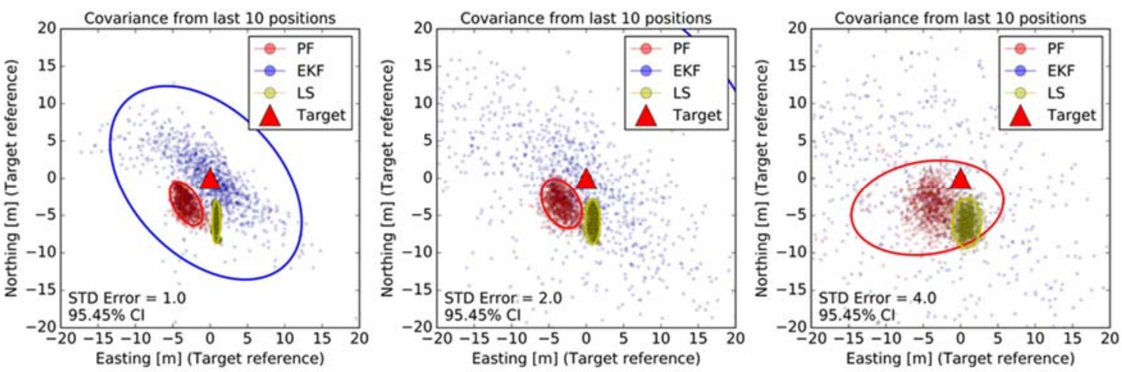

Fig. 5. Representation of the algorithms' covariance error in three scenarios: low-noise, middle-noise and high-noise levels, which have a STD of 1 m, 2 m, and 3 m respectively. These values have been obtained with a simulation 100 iterated, and using the last 10 estimations of each iteration.

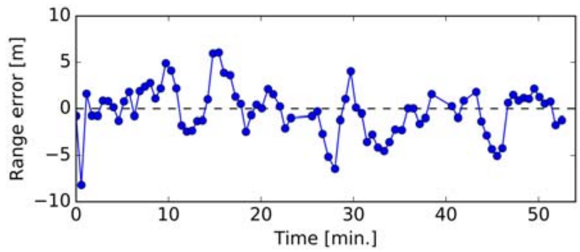

Fig. 6. Range error obtained during the OBSEA test.

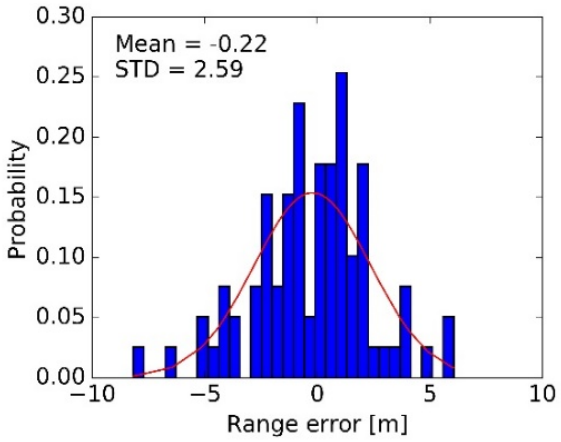

Fig. 7. Range error histogram obtained during the OBSEA test, which have an error mean of -0.22 meters and a Standard Deviation (STD) of 2.59 meters.

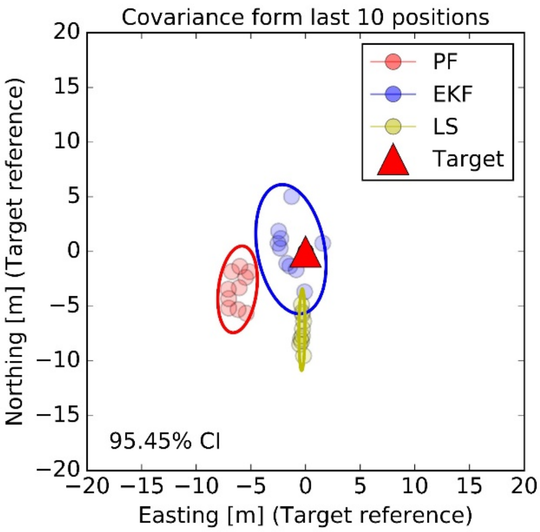

Fig. 8. Representation of the last 10 target estimations during the OBSEA test, using the PF, EKF and LS algorithms. Ellipse circumference shows the points' covariance.

Table 1. Standard deviation and mean error of a target position estimation using LS, EKF, and PF algorithms, in three different noise scenarios (simulated). Values in meters.

	Noise level	STD of vector 1	STD of vector 2	Mean
PF	1	0.85	1.61	4.68
PF	2	1.17	1.78	4.76
PF	4	5.13	3.11	5.94
EKF	1	4.95	7.65	0.83
EKF	2	13.87	15.89	5.21
EKF	4	23.68	23.21	17.9
LS	1	0.26	1.42	5.94
LS	2	0.49	1.47	5.91
LS	4	0.94	1.63	6.09

.

V. CONCLUSIONS

Range-only and single-beacon method for underwater target localization and tracking is interesting for its low complexity deployment, and can be used in a wide ocean area. Moreover, this method can be used in multi vehicle collaboration or in an underwater sensor network. For this reason, different studies have been done during the resent years.

This paper have been studied the accuracy and precision that can be obtained using Least Square (LS), Extended Kalman Filter (EKF), and Particle Filter (PF) methods, conducting both simulations and field tests. We could observe that whereas the EKF have an important dependency with the noise level, both PF and LS methods have a bigger robustness. These last algorithms have a good precision, with a small standard deviations between estimations. However, they suffer from some bias, and therefore, it should be compensated to obtain a better accuracy.

As a future work, these algorism will be tested in a moving target, and more filed test will be carried out to study other aspects such as speed rate and setting time.

VI. ACKNOWLEDGMENT

This work was partially supported by the project NeXOS from the European Union's Seventh Programme for research, technological development and demonstration under the grant agreement No 614102. We also had financial support from the Spanish Ministerio de Economía y Competitividad under contract CGL2013-42557-R (Interoperabilidad e instrumentación de plataformas autónomas marinas para la monitorización sísmica, INTMARSIS) and CTM2015-68804-REDT (Instrumentation and Applied Technology for the Study, Characterization and Sustainable Exploration of Marine Environment, MarInTech). The main author of this work has a grant (FPI-UPC) from UPC for his PhD research.

REFERENCES

[1] D. Moreno-Salinas, N. Crasta, M. Ribeiro, B. Bayat, A.M. Pascoal, J. Aranda, “Integrated Motion Planning, Control, and Estimation for Range-Based Marine Vehicle Positioning and Target Localization,” IFAC-PapersOnLine, Volume 49, Issue 23, 2016, Pages 34-40, ISSN 2405-8963

[2] I. Masmitja, S. Gomariz, J. Del Rio, B. Kieft and T. O'Reilly, "Range-only underwater target localization: Path characterization," OCEANS 2016 MTS/IEEE Monterey, Monterey, CA, 2016, pp. 1-7.

[3] I. Masmitja, O. Pallares, S. Gomariz, J. Del Rio, T. O'Reilly and B. Kieft, "Range-only underwater target localization: error characterization," 21st IMEKO TC4 International Symposium and 19th International Workshop on ADC Modelling and Testing Understanding the World through Electrical and Electronic Measurement, Budapest, Hungary. pp. 267-271, 2016.

[4] JCGM 200:2012 “International Vocabulary of Metrology – Basic and General Concepts and Associated Terms (VIM),” 3rd edition

[5] S. D. McPhail and M. Pebody, "Range-Only Positioning of a Deep-Diving Autonomous Underwater Vehicle From a Surface Ship," Journal Of Oceanic Engineering, vol. 34, no. 4, pp. 669-677, 2009.

[6] M. Stojanovic, "On the Relationship Between Capacity and Distance in an underwater acoustic communication channel," in WUWNet '06 Proceedings of the 1st ACM international workshop on Underwater networks, New York, 2006.

[7] K. G. Kebkal, A. K. Kebkal and G. A. Ermolin, "Mathematic and experimental evaluation of phase errors when receiving hydro-acoustic PSK-signals with sweep-spread carrier in reverberant underwater environments," 2013 MTS/IEEE OCEANS - Bergen, Bergen, 2013, pp. 1-8.

[8] E. Olson, J. J. Leonard and S. Teller, "Robust Range-Only Beacon Localization," Journal Of Oceanic Engineering, vol. 31, no. 4, pp. 949-958, 2006.

[9] S. Gomariz, I. Masmitja, J. González, G. Masmitja, J. Prat, “GUANAY-II: an autonomous underwater vehicle for vertical/horizontal sampling,” Journal of marine science and technology. Vol. 20, num. 1, p. 81-93. 2015 doi:10.1007/s00773-013-0253-y

[10] A. Alcocer, “Positioning and Navigation Systems for Robotic Underwater Vehicles,” PhD thesis, Universidade Tecnica de Lisboa Instituto Superior Tecnico, Dynamical Systems and Ocean Robotics Lab (DSOR), 2010

[11] A. Jazwinski. “Stochastic processes and filtering theory”. Academic Press, 1970

[12] [Thomas B. Schon, “Solving nonlinear state estimation problems using particle filters--an engineering perspective,” 2010. Technical Report. Automatic Control at Linkopings Universite

[13] www.obsea.es