# Detection and Tracking of tagged Marine Animals

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Abstract—This work was motivated by the MAST/AM project, whose objective is to develop a more practical alternative to the available comercial positioning systems, being composed by a Surface Robotic Tool and a Portable Tool. Instead of using an acoustic sensor network, these robotic tools are based on USBL sensor arrays which will allow for an online detection of aquatic animals marked with acoustic tags as well as permitting an estimation on the Direction-of-arrival of the signal. The signal detection uses an IIR filter and a simple threshold comparison, whilst the estimation of the Direction-of-arrival is based on a computationally efficient closed form solution. Furthermore, this paper discusses an offline processing method to combine the saved detection data and direction estimates in order to get an estimate on the position of the tagged animal and to track its movements over time using a Kalman filter. Finally, a simulation allows to demonstrate the previously described strategies of detection and tracking taking into consideration a spherical propagation model permitting therefore to conclude that the proposed system is at least in simulation comparable to a commercial positioning system in what concerns its detection range and localization precision.

Index Terms—acoustic tags, Acoustic propagation, IIR filters, Direction-of-arrival estimation, Kalman filters.

#### I. INTRODUCTION

**C** OMERCIAL systems for localization of tagged aquatic animalsare often based on a network of several receivers which are deployed on fixed moorings. The difficulties arising from the receiver installation as well as the complexity of the data recovery and analysis, which creates a dependency on manufacturer's services, led the *MAST/AM* project to purpose a new system, capable of detecting and tracking the movement of animals that are marked with acoustic tags.

This new system is to be composed by a Surface Robotic Tool located on a buoy at the sea surface as well as a Portable Tool, which is to be used by a diver. These tools are very similar in their setting, since both are capable of detecting a marked marine animal and both can estimate the Directionof-arrival (DOA) of the emitted acoustic signal since both of them use a Ultra-Short-Baseline (USBL) receiver array. Thus, these tools are suited for active tracking missions. Additionally they permit two possible application scenarios to track the movement of the detected animals after the mission has ended. Either the Portable Tool can be used alone or both tools are used together. In the first case it is necessary that the tag, which is implanted or attached to the marine animal, emits not only its identifying ID but also a depth estimate from a local sensor. In the latter case the direction estimates of each of the tools are combined in order to estimate the animal's position. A post processing of the acquired detection data allows the application of a Kalman filter to compensate for weak or missing measurements.

Having in mind the limiting nature of acoustic propagation in the aquatic medium, the *MAST/AM* project purposed to achieve a localization precision of about 1 to 2 meters for distances of 600 to 1000 meters using both tools. Furthermore, the equipment should have an autonomy of 3 to 4 hours and should be able to give a location estimate every 1 to 5 seconds. [1]

For comparison, a comercial positioning system for *passive tracking* scenarios can achieve a localization precision of 1 to 2 meters when great effort is invested into the installation of the sensor network but usually has a precision of 5 to 10 meters. The distances at which the tags can be detected range from 300 to 1000 meters depending on the specific conditions, which defines the maximum distances at which the receivers need to be installed since their detection ranges are required to overlap. [2] [3]

#### **II. SIGNAL PROPAGATION**

The propagation of the signal in the aquatic medium has a decisive influence on the performance of the system. The main factors impacting on subaquatic acoustic communication are attenuation and multipath propagation as well as inhomogeneities in the propagation characteristics of the aquatic medium.

In many acoustic communication applications attenuation is one of the most limiting influences. Considering a point like source with no imposed boundaries and a constant sound velocity medium, the propagation can be modeled as being spherical causing attenuation in the signal amplitude proportional to the square of the radius r from the source. This can be expressed in dB as

$$TL = 20 \log\left(\frac{r}{r_{1m}}\right) + \alpha r,\tag{1}$$

where  $\alpha$  represents an additional attenuation coefficient usually expressed in dB/km. This attenuation coefficient considers chemical processes of dilatation of magnesium sulfate  $(MgSO_4)$  and boric acid  $(B(OH)_3)$  as well as the viscosity of pure water. Its value can be determined by the model of *Francois* and *Garrison*. For more detail, it is recommended to consider the literature indicated under [4].

Due to the relatively slow propagation velocity of sound in water, generally between 1450 m/s and 1550 m/s, multi-path propagation is a much bigger issue in underwater communications than in communications with electromagnetic radio waves. Natural borders like the water surface, the sea ground and any objects in the water like riffs or rocks can create echoes, which propagate on alternative paths and reach the receiver from different directions. Therefore the creation of multi-path propagation strongly depends on the environmental conditions. At the receiver the echoes can be mistaken as part of the original signal or create interference that difficult the signal detection. This is specially a problem when the signal detection involves the detection of times of arrival of single tone pulses.

Factors like pressure, temperature and salinity influence the propagation speed of sound in water. Variations to these factors in the water column will create refraction in the propagation path. As a consequence sound will not obligatorily propagate in a rectilinear or predictable way and the wave front cannot always be considered as a plane wave, even at big distances from the source.

Yet another potential problem for surface located receivers is caused by air bubbles created by surface disturbances. They form upper inhomogeneous layers with strong local variability in the sound speed. Besides an additional attenuation air bubbles will have a scattering effect and will be responsible for small parasite echoes at the receiver. Depending on the size of the air bubbles, their number and distribution, they can create serious difficulties in acoustic communications.

#### **III. DIRECTION-OF-ARRIVAL ESTIMATION**

The *Direction-of-arrival* (*DOA*) of an acoustic signal can be estimated using the *TDOA* of the incident acoustic wave on the various hydrophones of the *USBL* sensor array. Following the approach presented in [5] and already used in [6], the planar wave approximation is used and a medium of constant propagation velocity is assumed.

To estimate a *Direction-of-arrival* at least three sensors are needed, although more than three sensors are recommended for purposes of redundancy. Figure 1 depicts the XY-plane of the hydrophone array with two of its N sensors (*i* and *j*) and an arriving planar wave front at the arrival moments  $t_i$  and  $t_j$ . The unitary vector  $d = [d_x \ d_y \ d_z]^T$ ,  $(||d||_2 = 1)$ , points towards the *DOA* of the acoustic wave and it is the quantity to be estimated in this problem.



Figure 1: Projection on the XY plane of a planar acoustic wave front arriving at two receivers [6]

Considering the positions of the two sensors i and j, given by  $r_i = [x_i \ y_i \ z_i]^T$  and by  $r_j = [x_j \ y_j \ z_j]^T$  and the constant propagation velocity  $v_p$ , we come to the following relation:

$$v_p(t_i - t_j) = -d^T(r_i - r_j).$$
 (2)

Considering eq. 2 and generalizing for N sensors with

$$\{i = 1, 2, ...N ; j = 1, 2, ...N ; i \neq j\}$$
(3)

one may define

$$\Delta = [\Delta_1 \ \Delta_2 \ \dots \ \Delta_M]^T, \tag{4}$$

with  $\Delta_1 = t_1 - t_2$ ,  $\Delta_2 = t_2 - t_3$ , ...  $\Delta_M = t_{N-1} - t_N$ representing the *TDOA* for all possible *M* pairs of sensors which can be generated by

$$\Delta = Ct_m. \tag{5}$$

where C is a combination matrix and  $t_m$  is a vector of TOA.

Similarly S describes the differences of positions of all possible M pairs of sensors and can be written as

$$S = \begin{bmatrix} x_1 - x_2 & y_1 - y_2 & z_1 - z_2 \\ x_1 - x_3 & y_1 - y_3 & z_1 - z_3 \\ \vdots & \vdots & \vdots \\ x_{N-1} - x_N & y_{N-1} - y_N & z_{N-1} - z_N \end{bmatrix}.$$
 (6)

The generalization of equation 2 can therefore be written as

$$v_n \Delta = -Sd \tag{7}$$

with its least squares solution

$$d = -v_p S^{\#} C_{tm} \tag{8}$$

where  $S^{\#}$  is the pseudo inverse of S and it is given by  $S^{\#} = (S^T S)^{-1} S^T$ . The unitary vector d is the estimate of the DOA of the acustic wave to the sensors of the USBL sensor array.

### IV. POSITIONING

Depending on the scenario, either both the *Surface Robotic Tool* and the *Portable Tool* or just one of them, may be used for tracking purposes.

When only one *USBL* is used, and therefore only one *DOA* estimate is available, it is necessary to use tags with sensor information in order to be able to locate them. In addition to its *ID* and the corresponding *Checksum*, the tag might transmit a pressure measurement or a directly calculated depth estimate, as it happens with the comercial tags (compare [7]).

In an idealized environment and disregarding the variability found in the pressure profile of an ocean normally caused by its currents, the pressure p at a given depth h is related to the hydrostatic pressure of the water column above it and is given as

$$p = h\rho g, \tag{9}$$

where  $\rho$  is the density of the aquatic medium and g represents the gravitational acceleration.

In order to calculate an estimate of the fish's position it is enough to calculate the intersection of the line given by the *USBL* position and the estimated *DOA* of the detected signal with the horizontal plane defined by the depth estimate of the tag. When the line and the plane are parallel to each other it is impossible to calculate an estimate of the fish's position.

When the *Surface Robotic Tool* and the *Portable Tool* are simultaneously used no additional sensor data is needed from the tag. In this case the two lines formed by the *USBLs'* positions and their corresponding *DOA* estimates can be used to either calculate their intersection point or to obtain the nearest point to both of these lines. This point will then serve as an estimate on the position of the tagged animal. If both lines are parallel to each other no estimate can be obtained.

It is worth mentioning that the *DOA* estimates are calculated locally on each *USBL* which makes a coordinate transformation necessary to obtain a *DOA* in a common coordinate system. Once this has been accomplished, the nearest point to two lines is found, as has been described in [8], in the following way: Considering two lines  $L_1$  and  $L_2$  given as

$$\mathbf{L}_{1}: P(s) = P_{0} + s(P_{1} - P_{0}) = P_{0} + s\mathbf{u}$$
(10)

$$\mathbf{L}_{2}: Q(t) = Q_{0} + t(Q_{1} - Q_{0}) = Q_{0} + t\mathbf{v}$$
(11)

and a vector  $\mathbf{w}(s,t) = P_s - Q_t$  joining two points, one point on each of the two lines, the two points on both lines nearest to each other,  $P_C$  and  $Q_C$ , are those, for which the joining vector  $\mathbf{w}(s_c, t_c)$  is perpendicular to vector  $\mathbf{u}$  as well as to vector  $\mathbf{v}$  and therefore  $\mathbf{u} \cdot \mathbf{w_c} = 0$  and  $\mathbf{v} \cdot \mathbf{w_c} = 0$ . Figure 2 shows the relation between vector  $\mathbf{w}(s_c, t_c)$  and the two lines  $L_1$  and  $L_2$ 



Figure 2: Visualization for the two closest points  $P_c$  and  $Q_c$  on two non-crossing lines. [8]

These two equations can be solved by substituting  $\mathbf{w_c} = P(s_c) - Q(t_c) = \mathbf{w_0} + s_c \mathbf{u} - t_c \mathbf{v}$ , with  $\mathbf{w_0} = P_0 - Q_0$ , into both equations, leading to:

$$(u \cdot u)s_c - (u \cdot v)t_c = -u \cdot w_0 \tag{12}$$

$$(v \cdot u)s_c - (v \cdot v)t_c = -v \cdot w_0 \tag{13}$$

Taking  $a = \mathbf{u} \cdot \mathbf{u}$ ,  $b = \mathbf{u} \cdot \mathbf{v}$ ,  $c = \mathbf{v} \cdot \mathbf{v}$ ,  $d = \mathbf{u} \cdot \mathbf{w}_0$ , and  $e = \mathbf{v} \cdot \mathbf{w}_0$ , and solving for  $s_c$  and  $t_c$ , the solution is given by:

$$s_c = \frac{be - cd}{ac - b^2}$$
 and  $t_c = \frac{ae - bd}{ac - b^2}$ . (14)

Note that  $ac - b^2 = |\mathbf{u}|^2 |\mathbf{v}|^2 - (|\mathbf{u}||\mathbf{v}|cos\theta)^2 = (|\mathbf{u}||\mathbf{v}|sin\theta)^2 \ge 0$ . When  $ac - b^2 = 0$  the two equations are dependent and the two lines are parallel leading to a situation in which it is not possible to estimate the position of the tagged animal. Having determined  $s_c$  and  $t_c$  it is easy to calculate  $P_c$  and  $Q_c$  and consequently to obtain the nearest point to both lines given by  $P = (Q_c - P_c)/2$ .

In a certain way the distance between  $P_c$  and  $Q_c$  gives an idea of the possible quality of the measurement because a measurement obtained by two USBLs pointing towards a similar origin is more trustworthy than a measurement obtained by two USBLs pointing to different locations.

## V. ANIMAL TRACKING

The Kalman Filter is an algorithm for the optimal estimation of the state of a system when some noise corrupted measurements and a linear model of the system are given. Therefore this filter is an appropriate tool to estimate the motion of a tagged fish and to join the measurements obtained by the *Surface Robotic Tool* and the *Portable Tool* with an internal model of the fish's movement.

## A. Kalman Filter

As already mentioned, the Kalman filter is based on an internal model of the fish's movement as well as on a measurement model. In the discrete version these models are given by the following equations:

$$\bar{x}_{k+1} = \Phi_k \bar{x}_k + \Gamma_k \bar{w}_k$$
 Process model (15)

$$\bar{z}_k = H_k \bar{x}_k + \bar{v}_k$$
 Observation model (16)

The Kalman filter uses the *Process model* in high frequency when no measurement is available to estimate the state of the system in a *Prediction Step* and makes use of the *Observation model* to incorporate an available measurement into the existing state estimate during an *Update Step*. Along with the state estimate, the Kalman filter keeps an estimate of its covariance along time as well so that the current measurement can be weighted in relation to the prior state estimate.

The state estimate prior to the incorporation of any new measurement is denoted by  $\hat{x}^-$  where the hat refers to it being an estimate and the upper minus indicates that it is prior to incorporating a measurement.

The equations that define the Kalman filter are given by:

$$K_{k} = P_{k}^{-} H_{k}^{T} [H_{k} P_{k}^{-} H_{k}^{T} + R_{k}]^{-1} \quad \text{Kalman gain} \quad (17)$$

$$\hat{x}_k = \hat{x}_k^- + K_k [z_k - H_k \hat{x}_k^-]$$
 State update (18)

$$P_k = [I - K_k H_k] P_k^- \quad \text{Covariance} \quad (19)$$
  
update

 $\hat{x}_{k+1}^{-} = \Phi_k \hat{x}_k$  State prediction (20)

$$P_{k+1}^{-} = \Phi_k P_k \Phi_k^T + \Gamma_k Q_k \Gamma_k^T \quad \text{Covariance} \quad (21)$$
  
prediction

#### B. System Model

An appropriate model to describe the movement of a fish is given by a constant acceleration movement, that is, it is assumed that the fish will keep its tendency of movement by keeping the same acceleration as it had some instants before. This can be expressed by the discrete equations 22 to 24 with  $\Delta t$  being the elapsed time between iterations k and k + 1, p representing the position, v the velocity and a the acceleration of the animal.

$$p_{k+1} = p_k + v_k \Delta t + \frac{1}{2} a_k \Delta t^2 \tag{22}$$

$$v_{k+1} = v_k + a_k \Delta t \tag{23}$$

$$a_{k+1} = a_k \tag{24}$$

The state of the system is consequently describing the position, velocity and acceleration of the fish in three dimensional space, as in the vector given by

$$\bar{x} = \begin{bmatrix} p_x & p_y & p_z & v_x & v_y & v_z & a_x & a_y & a_z \end{bmatrix}^T.$$
 (25)

Using matrix notation and discriminating equations 22 to 24 for three dimensions, the resulting System model is given by

$$\bar{x}_{(k+1)} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 & \frac{1}{2}\Delta t^2 & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \frac{1}{2}\Delta t^2 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \frac{1}{2}\Delta t^2 \\ 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \bar{x}_k + \bar{w}$$

(26)

(27)

Obviously a real fish will not keep constant acceleration during all time. Therefore it is necessary to have a system model that allows for some noise, in order to react to variations in the movement of the animal. As smooth movements are desired as well as an adjustment of the constant acceleration model, the noise vector  $\bar{w}$  in the model will only consider for noise in the acceleration components. Consequently the covariance matrix  $Q_k$  describes the way, this noise is propagated in the estimate due to the system model and is given by:

$$Q_k = \begin{bmatrix} \frac{1}{4}\Delta t^4 & 0 & 0 & \frac{1}{2}\Delta t^3 & 0 & 0 & \frac{1}{2}\Delta t^2 & 0 & 0\\ 0 & \frac{1}{4}\Delta t^4 & 0 & 0 & \frac{1}{2}\Delta t^3 & 0 & 0 & \frac{1}{2}\Delta t^2 & 0\\ 0 & 0 & \frac{1}{4}\Delta t^4 & 0 & 0 & \frac{1}{2}\Delta t^3 & 0 & 0 & \frac{1}{2}\Delta t^2\\ \frac{1}{2}\Delta t^{30} & 0 & 0 & \Delta t^2 & 0 & 0 & \Delta t & 0\\ 0 & 0 & \frac{1}{2}\Delta t^3 & 0 & 0 & \Delta t^2 & 0 & 0 & \Delta t & 0\\ \frac{1}{2}\Delta t^2 & 0 & 0 & \Delta t & 0 & 0 & 1 & 0 & 0\\ \frac{1}{2}\Delta t^2 & 0 & 0 & \Delta t & 0 & 0 & 1 & 0\\ 0 & \frac{1}{2}\Delta t^2 & 0 & 0 & \Delta t & 0 & 0 & 1 & 0\\ 0 & 0 & \frac{1}{2}\Delta t^2 & 0 & 0 & \Delta t & 0 & 0 & 1 \end{bmatrix} q_{mag}^2$$

The parameter  $q_{mag}$  needs to be adapted to fit the behavior of the fish which can be a difficult task since different types of fish tend to behave differently In the same way, the covariance matrix describing the sensor noise requires some calibration but can generally be assumed to follow the following pattern where the values for  $r_{ii}$  need to be adjusted.

$$R_k = \begin{bmatrix} r_{xx} & 0 & 0\\ 0 & r_{yy} & 0\\ 0 & 0 & r_{zz} \end{bmatrix}$$
(28)

The measurement method does not return measures for all state variables, but just for the position. Consequently the covariance matrix for the sensors  $R_k$  has 3 by 3 dimensions and the matrix H describing the observation model is given by:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$
(29)

Having defined all integral parts of the Kalman filter, its implementation is straight forward.

## VI. SIMULATION

The basic functioning principles of the above mentioned detection and tracking strategies are demonstrated in a simulation. According to the two identified scenarios, the simulation may be carried out with one or two *USBLs* in order to be able to identify and locate a marked animal. The movement of this marine animal may be described either as a trajectory through a series of points or according to a movement model of the animal. At the end of the simulation an output file "*output.txt*" is generated containing the estimated directions, the spherical angles and the measured points.

The simulation was implemented according to the objectoriented programming paradigm. In this way the source code is organized in logical units, simplifying the maintenance of the code and making it easier to understand. The most important objects used and defined in the simulation are the following:

*Fish*: contains an *ID* that identifies the individual fish, and the corresponding emitted signal encoding the *ID*.

**Channel:** adds two types of white Gaussian noise to the signal emitted by the fish. The first type simulates the noise, which is added to the signal in the aquatic medium, the second type simulates the intrinsic noise to the hydrophones that are used as sensors to the system. It is also responsible for the attenuation of the signal through a spherical or a cylindrical propagation model, taking into account the absorbtion model of *Francois* and *Garrison*. The channel further delays the signal in time to simulate the propagation to each of the four hydrophones.

**Event:** symbolizes the emission by a fish and the detection by an USBL of a signal. It contains information on the *fish* that originated the event: *ID*, signal, position and time instant.

**Event List:** manages the *Events* and maintains them in chronological order. When two *Events* are queued one after the other in a time window of less than 4 seconds the *Event List* joins them to a single signal event. This operation corresponds to a collision of two signals and as a result the original signals are not detected by the *USBLs*. The *USBLs* receive the *Events* from the *Event List*.

**USBL:** detects a noise-corrupted signal and decodes it. The USBL returns the identified *ID* and *Checksum* as well as the direction estimate.

*System:* contains the simulation's main logic managing all other objects and organizing their interactions. It generates the graphical display of the results and the printing of the output file *"output.txt"*.

**Detection:** combines the *Event* with its detection in an *USBL* keeping track of metrics of detection quality. The *precision* measures the distance between the two lines defined by the direction estimates given by the two *USBLs*. Although it is not an accurate quality indicator for the measurement itself, it is a good estimate for the confidence of a single detection. The bigger the value is the less will be the confidence in the measurement. The *error* measures the distance between the fish's real position given at the moment of an *Event* and the position measured by the *System* indicating the real quality of the measurement.

**Fish Model:** is a simulation intern model to estimate the position of the *Fish*. After the detection of a *Fish* a model is created for this *Fish* or updated in case it already exists. This model uses the *Kalman Filter*, which makes possible a prediction or an update of the state estimate.

Diagram 3 visualizes the tasks carried out by the different objects and the interaction between them.



Figure 3: Schematic overview on the interactions between the individual objects that make part of the simulation

# VII. SIMULATION RESULTS

The simulation permits to evaluate the range in which signal detection is feasible considering the constraints of acoustic propagation. Similarly the method to locate detected animals can be assessed in terms of its accuracy. Furthermore it is possible to demonstrate situations of signal collision and to compare different configurations for the Kalman filter.

# Signal Detection

The performance of the detection algorithm is influenced by several factors, nevertheless the *SNR* has the biggest influence on signal detection. With age the battery of the tags will loose power and with it the quality of the emitted signal will deteriorate. A signal with lower amplitude will have a lower *SNR* and is therefore more difficult to detect by threshold comparison. Likewise, keeping the same amplitude of the signal but increasing the noise will also lower *SNR* and thus hamper signal detection. The comercial tags generally present an emitting power of 136 to 162  $dB re 1\mu Pa$  @1m [9] depending on the tag model, which allows them to be detected at large distances, in which the detection range is mainly limited by the attenuation during signal propagation. A simplistic but appropriate and often used model for the acoustic propagation is the spherical propagation model. Depending on the environmental conditions, other models like the cylindrical propagation model with less attenuation might be more suiteable. The simulation does not regard multi-path propagation, which could represent a serious threat to the detection of *TDOAs*, but is able to show the effect of the previously mentioned factors on signal detection using the seven *tags* available for simulation. Table I sumarizes the obtained results.

Despite of the fact that the simulation does not allow to change the threshold, it should become clear that the performance of the detection algorithm also heavily depends on a propper choice of the threshold level.

Table I: Comparison of the detection range for different *SNRs* at the receiver for some simulated *tags*, considering a spherical propagation model and additional attenuation according to the absorption model of *Francois* and *Garrison*. (Assumed are: *USBL* and tag depth of 50*m*, salinity of 35 *p.s.u.* and temperature of  $15^{\circ}$ C)

ID	Range	SNR - Source	Attenuation	SNR - Receiver
	(m)	(dB)	(dB)	(dB)
С	250	63,5	48,0	15,6
	70	49,5	36,8	12,7
	33	43,5	30,1	13,4
D	780	68,0	57,9	10,1
	206	54,0	46,3	7,7
	125	48,0	41,9	6,1
А	57	54,0	35,0	19,0
	18	40	24,6	15,4
	9	34,0	18,1	15,9
В	17	48,0	24,1	23,9
	6	34,0	14,0	20,0
	3	28,0	6,0	21,9
Е	105	63,5	40,4	23,2
	37	49,5	31,2	18,4
	16	43,5	23,5	20,0
F	545	66,0	54,7	11,3
	163	52,0	44,2	7,8
	85	46,0	38,5	7,5
G	575	66,0	55,2	10,8
	155	52,0	43,8	8,3
	90	46,0	39,0	7,0

## Animal Tracking

The algorithm for *Direction-of-arrival* estimation has a good performance being able to indicate the *DOA* in spherical coordinates with a precision of 0,1 to 0,2 degrees.

When only one USBL is used in combination with a depth sensor tag, the localization precision of the system is mainly dependent on the precision of the depth estimate given by the tag which can largely vary depending on the specific tag and varying from  $\pm 1.7$ m up to  $\pm 34$  m for the comercial tags [7].

In the case that two *USBLs* are used for localization the localization method requires the intersection of two lines. Through simulation it is possible to show that the used localization method can sometimes achieve a precision of about 1 to 2 meters, but has a precision between 5 to 10 meters for distances of 600 to 1000 meters in most of the cases, as can be seen in fig. 4, 5 and in fig. 6, 7.



Figure 4: Graphical representation of the measurements (red), predictions (black) and updated estimates (green) on the animal's position in comparison with its real trajectory (blue). (Fish ID: D)



Figure 5: The localization method and the corresponding position estimate generally achieve an accuracy better than 10 meters for distances between 600 and 1000 meters. (Fish ID: D; precision - blue; measurement error - green; estimation error - red)

The introduction of the Kalman filter does not significantly improve the system's localization precision. Sometimes the estimate even gets worse than the measurement. This is because it is extremely difficult to adjust the Kalman filter with its matrices and noises to the tracked movement. Still, the Kalman filter is useful to obtain position estimates in a higher rate than the measurement rate and it also allows for a position estimate in the case of signal collision. This is shown in Fig. 8 where signal collisions in the fishes' tracks are marked with red circles.

# VIII. CONCLUSIONS

A system was described to detect and track marine animals that are tagged with comercial acoustic tags.



Figure 6: Graphical representation of the measurements (red), predictions (black) and updated estimates (green) on the animal's position in comparison with its real trajectory (blue). (Fish ID: C)



Figure 7: The localization method and the corresponding position estimate can occasionally achieve an accuracy better than 5 meters. (Fish ID: C; precision - blue; measurement error - green; estimation error - red)

The nature of subaquatic sound propagation burdens many risks to the system's performance and the different environmental conditions have an essential influence. Inhomogeneities in the salinity, pressure or temperature profile can cause refraction and thus invalidate the assumptions of a planar and rectilinear propagation which are the fundament of the method used to estimate the *Direction-of-arrival* of the signal. Furthermore, the effect of air bubbles in the surface layer and multi-path propagation present other critical factors that can negatively influence the proper functioning of the system. These factors have not been considered in the simulation but it was possible to evaluate the system's performance concerning the detection range of a tag and the precision of the localization method taking into account *AWGN* in the channel and the attenuation inflicted on the signal.

The detection range of the tags could be confirmed to correspond to the estimates given by the manufacturer and it also shows that the range stipulated by the *MAST/AM* project of 600 to 1000 meters is realistic but that it largely depends on the environmental conditions and on the signal quality which deteriorates with the age of the tags.

When applying only one *USBL* in combination with a tag that delivers sensor data, the performance of the localization



Figure 8: Signal collisions are shown as a red circle on the animal's track.

algorithm is largely dependent on the precision of the depth estimate of the tag ranging from  $\pm$  1,7m to  $\pm$  34 m depending on the specific sensor.

When applying two *USBLs* the performance of the system was found not to comply with the requirements of the *MAST/AM* project, which demands a precision of 1 to 2 meters on distances of 600 to 1000 meters, a precision which can only be achieved for shorter distances. In the case of 600 to 1000 meters the system's precision was between 5 and 10 meters and better results could only be obtained occasionally.

With the simulation of signal collisions it could be shown that in these cases the Kalman filter brings the advantage of being able to deliver a position estimate compensating missing measurements. It became also clear that the distance between two consecutive emissions is to large for the Kalman filter to significantly improve the position estimates since the system model accumulates to much uncertainty and the fish could meanwhile have changed its track. The use of the Kalman filter could be adequate for migration scenarios of tuna fish for example, in which the animal keeps a clear predominant direction of movement, but would be less worthy, if not prejudicial, in scenarios in which the animal does many abrupt changes in its movement or does not move a lot which could happen for example while feeding near a reef.

All in all, the system shows a comparable performance to the comercial positioning system, with the advantage of being easier in use and that it combines the possibilities of *active tracking* with those of *passive tracking* in just one system.

More factors of signal propagation could possibly be added to the simulation, bringing it closer to reality. Nevertheless real on field tests are indispensable to better evaluate the system's performance and its optimal application scenarios.

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