ROV NAVIGATION WITH MECHANICALLY SCANNED SONAR, DVL AND GYROSCOPE

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Abstract. *The task of navigating a Remotely Operated underwater Vehicles (ROV) during inspection of man-made structures is performed mostly by visual references and occasionally a magnetic compass. Yet, some environments present a combination of low visibility and ferromagnetic anomalies that negates this approach. This paper, motivated by the development of a ROV designed to work on such environment, proposes a navigation method for this kind of vehicle. As the modeling of the system is nonlinear, the method proposed uses a particle filter to represent the vehicle state that is a nonparametric implementation of the Bayes filter. This method to work needs a priori knowledge of the environment map and to make the data association with this map, a mechanically scanned sonar is used as the main sensor. Besides the sonar, are also part of the navigation system, a Doppler Velocity Log (DVL) and a gyroscope. As the ROV is in its early stages of development, a floating platform was used in its place and because of that the estimation of the position in this work was restricted to the horizontal plane (since ROVs are usually statically stable on pitch and roll, this is a good approximation). The tests were conducted in a rectangular tank of know size, and even without a ground truth to validate the results, was possible to conclude that the propose navigation system can estimates planar position of the vehicle with great precision.*

Keywords: *ROV, Navigation, Particle Filter, Mechanically Scanned Imaging Sonar*

1. Introduction

Despite the increasing development of autonomous underwater vehicles (AUVs), many underwater applications yet rely on the use of remotely operated vehicles (ROVs),due to their complexity and therefore the need for an operator. ROV is a type of underwater robot which is connected with a base station on the surface by an umbilical cable that provides the power supply and commands. They usually have a video camera and a sonar to assist their operators in its navigation. But for some ROV's applications, like ship hull inspection, it is necessary to have a good accuracy of the location where the data were acquired. So even though this type of robot is not autonomous, it needs some semi autonomous functions, like a navigation system, to accomplish some missions.

The function of a navigation system is to estimate the current position and orientation of the robot based on current and past informations of some sensors. Thus, the development of a navigation system depends, among other factors, on the available sensors. By the fact that some sensors used in terrestrial robot navigation, do not work or have impaired functioning in underwater environments, is more complicated to develop a navigation system for a underwater robot that for a terrestrial one. An example of this is the GPS, which is widely used in terrestrial navigation, but because their signals don't propagate in the water, they can't be used in underwater environments. Another example are the video cameras that because the lack of visibility in underwater environments, they are also not an option.

As previously mentioned that the navigation system being developed depends on the available sensors, it is necessary to have a knowledge of the sensors used in underwater navigation (Kinsey *et al.*, 2006) . The most commonly used sensors in underwater environments are the inertial measurement unit, that measures the linear accelerations and angular velocities, and the Doppler Velocity Log (DVL) that measures the linear velocities (Leonard *et al.*, 1998). With these sensors it is only possible to estimate relative movements by numerical integration of their data and therefore to get a absolute positioning is necessary to know the initial position relative to a reference frame. The problem of these sensors is that their measures have errors and therefore the relative movement estimate given by them presents an error which increases gradually over time, making it necessary to merge with another sensor to correct them.

The solutions in underwater environments to make this correction are acoustic sensors. A first example of this type of sensor is the acoustic positioning that needs some transceivers around the region where the navigation will be made and a transponder in the vehicle to work (Matos *et al.*, 1999). This sensor has the same working principle of the GPS. There are several types of them and they differ on the number of beacons used to make the localization. The drawback of them is that they need a line of sight between the transceivers and the transponder and in some environments like man-made structure this may not happen, invalidating this kind of solution.

Another example of an acoustic sensor used in underwater environments to make the correction of the dead reckoning are the sonars. For underwater environments there are various types of sonar, there are sonars that have only one element as well as sonars that have multi elements. Also, there are sonars that measure only the distance to obstacles and there are sonars that in addition can measure the intensity of the returning echoes and thereby form an image of the environment (Ribas *et al.*, 2010).

Sonars that measures only the distance to obstacles are generally used in applications where some knowledge of the environment is available a priori, like when a bathymetric chart is available making it possible to correlate the measurement of distance from the seabed obtained by the sonar (Teixeira and Pascoal, 2008) or like when a structure map of the environment is available making it possible to correlate the measurement of a forwarding looking sonar (Kondo *et al.*, 2006). In relation to the sonar that provide an image of the environment, enables a navigation more complex as, for example, by extracting features from the environment and thus perform a Simultaneous localization and mapping (SLAM) (Fairfield *et al.*, 2007).

Having seen the sensors that are used in underwater environment is necessary to check a technique for making the fusion between them. A technique that is being widely used is the particle filter (Gordon *et al.*, 1993). This is because, the particle filter enables to work with nonlinear transformations in a simple way of implementation for being based on Sequential Monte Carlo method. The drawback of this kind of filter is its large computational cost if compared to others kind of filters. The particle filter has been extensively studied and nowadays exist many branches of this filter (Ristic *et al.*, 2004) such as different types of applications (Gustafsson *et al.*, 2002).

The aim of this paper is to present a navigation system for a ROV in an underwater environment compound with man made structures. As some environments of such type presents a combination of low visibility and ferromagnetic anomalies, these restrictions will be considered. With this restriction of sensors a sonar was considered to be the main sensor of the navigation system, with the dead reckoning of some sensors to assist it. To fuse the information acquired from those sensors, a particle filter will be used. A reasonably accurate map of the environment is also presumed to be available *a priori*.

This paper is structured as follows. Section 2. describes the particle filter used to fusion the sensors and so make the position estimate. The Section 3. and 4. describe respectively the motion model $p(x_t|x_{t-1}, u_t)$ and the measurement $p(z_t|x_t)$ which together with the initial state probability, forming the probability density functions necessary to implement the particle filter. The Section 5. shows the results obtained with real data from the sensors in a real scenario of the system proposed in this work. The paper ends with Section 6. that presents the conclusions and the future steps.

2. Particle filter

The problem of state estimation of a dynamic system addresses the problem of estimation quantities which are not directly observable, but can be inferred from noisy sensors. Thus in such problems, the equations describing the system are modeled by probabilistic laws. The probabilistic law that characterizes the evolution of the state is given by the following probability density function Eq. (1).

$$p(x_t|z_{0:t}, u_{0:t}) \tag{1}$$

The most common method used to calculate this probability density function is through a Bayesian filter. There are several ways to implement this type of filter, but when the system involves nonlinear transformations, the most common method used is the particle filter (Gordon *et al.*, 1993) that is a nonparametric implementation of it which is based on the sequential Monte Carlo method. The key idea is to represent the probability density function $p(x_t|z_{1:t}, u_{1:t})$ through a set of samples of this density with associated weights. These samples are called particles and each one represents a hypothesis on the state of the system so the greater the number of particles concentrated in a region of space most likely to this region to be the state real value. In this filter, the higher the numbers of particles used, the better will be the state estimation but also the computational cost to make it. With this approximation of the probability density functions through particles, particle filter allows to work with non linear transformations and non Gaussian distributions what it is not possible if used the more traditional method of navigation which is the Kalman filter.

As the Bayesian filter is a recursive filter, the particle filter is also recursive, thus the state estimation provided by the set of particles X_t is originated from the set of particle of the previous step X_{t-1} and the known inputs and outputs from the system. Also to be part of the Bayesian filters, each recursion of the particulate filter can be divided into two cycles, the predict cycle and the correct cycle. The predict cycle is responsible for projecting forward the state value using the state transition probability $p(x_t|u_t, x_{t-1})$ and the correct cycle is responsible to incorporate certain measurements of the system to improve the propagated state estimate using the measurement probability $p(z_t|x_t)$. So for its implementation it is necessary to know three probability density function, the initial state probability $p(x_0)$, the state transition probability $p(x_t|u_t, x_{t-1})$ and the measurement probability $p(z_t|x_t, m)$.

In this work was chosen the particle filter to perform the data fusion because of the nonlinearity of the motion and the measurement models, which will be discussed later, and also due to the possible of exploiting the parallelism of it. Nowadays there are several versions of the particle filter (Ristic *et al.*, 2004) and in this work was chosen the most common of them, that is the Sequential Importance Resampling (Thrun *et al.*, 2005).

2.1 Sequential Importance Resampling

This section presents a brief explanation of the Sequential Importance Resampling (SIR) (Thrun *et al.*, 2005). The SIR is a type of implementation of the particle filter which is a junction of another type of implementation of the particle filter, that is the Sequential Importance Sampling (SIS), with a resampling step.

As state in Section 2., the particle filter is recursive filter and thus the inputs to the algorithm are the set of particles of the previous step X_{t-1}, the control action u_t and the sensors measurements z_t and the output is the posterior set of particles X_t.

The first step of the algorithm is to generate a set of particles $\bar{X}$ that has each of their particles being generated from a particle of X_{t-1} and adding the influence of the control action u_t on it by sampling the state transition probability $p(x_t|u_t, x_{t-1})$. Then for each particle $x_t^{[m]}$ in $\bar{X}$ is calculated an importance weight $w_t^{[m]}$ which is based on measurement probability $p(z_t|x_t^{[m]})$. The particles propagated that present a greater resemblance to the measurement z_t will receive higher weights indicating that they represent the real state value better. Therefore, the weights have the function of incorporate the measurements z_t in the estimation of the state.

The steps described so far are part of the Sequential Importance Sampling (SIS). This method is no longer used because it presents an inefficient. The inefficiency comes from the fact that as this filter estimates the state by means of a processing in all the particles and in each iteration of the filter more and more particles ending up in regions of the state space far from real value of the state due to the Monte Carlo characteristic of the filter which is represented by the low values in the importance weights of these particles, the estimate of the state ends up having a waste of computational resource because processing wasted with these particles that are far from the real value of the state. For this reason, a resampling step was included in this process.

Then the algorithm ends performing the resampling step. This step consists in a sampling with replacement from the set of particles $\hat{x}_t^{[m]}$. This sampling is made according to the importance weights of the particles, the greater the weight of the particle the grater the chance of it being sampled. For the fact that this step is a sampling with replacement, it keeps the size of the set of particles and so the resulting set of particles may have some equal particles. So the reason for the resampling step is to focus the set of the particles in the region of the state space of greater relevance. By doing so, it keeps the number of particles of the filter limited and the computational resources bounded compared with SIS. To complement the explanation of the SIR, Fig. 1 illustrates the steps of it.

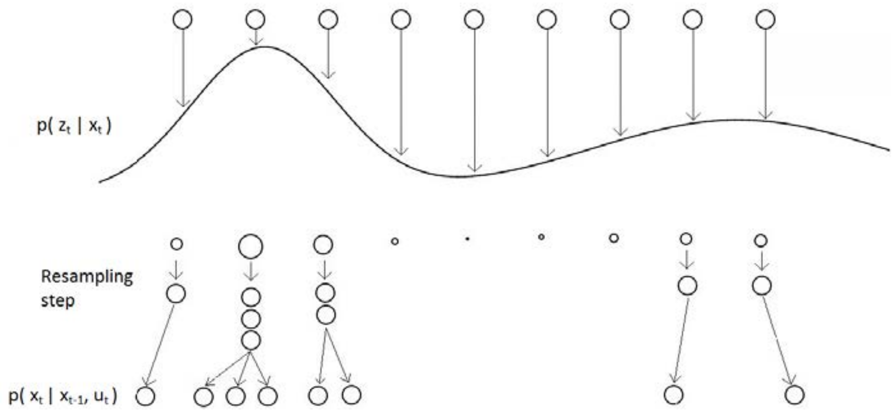

Figure 1. Steps of the Sequential Importance Resampling filter

2.2 Resampling

Although the resampling step is required to keep the number of particles of the filter bounded because it eliminates the particles that are remote from the region most likely to be the actual value of state, concentrating the resources of the filter in the regions of greatest relevance, extra care need to be taken with this step of the SIR. This because, if a non-modeled error is present in the sensor data used to calculate each particle's importance weight, these weights will lead to a state estimation inconsistent with the system actual state. Thus the particle set will converge to a wrong region of the state space, precluding the filter to return to the correct region of the state space.

To avoid this potential problem of the resampling step presented in Section 2.1, it is necessary to modify the way that it choose the particles or restrict its execution to only those cases where it is really needed. There are various ways to do that (Ristic *et al.*, 2004) and in this work was adopted a solution proposed in (Thrun *et al.*, 2005) named Low Variance Sampling. This method proposed in (Thrun *et al.*, 2005) differ from the resampling step explained in Section 2.1 because in the latter, all the particles have their weights normalized so the process to sample them is to make several samples from an uniform distribution on the $[0, 1]$ interval. With Low Variance Sampling, instead of using several sampled numbers to select the particles, it samples only one number and with it makes the selection of the particles but still considering their importance weights. Thus, the sampling process can go through the state space in a more broader way, avoiding the problem described above. To better understand the Low Variance Sampling, the Fig. **??** shows a pseudocode for it.

Algorithm 21: LowVarianceSampler($vector < particle > X_t$)

$vector < particle > newX_t$;

$M = X_t.size()$;
$r = UniformlyRandom(0, 1/M)$;
$c = X_t[0].weight$;
$i = 0$;

for $m \leftarrow 0$ **to** M
do $\begin{cases} U = r + (m-1) * (1/M); \\ \textbf{while } U > c \\ \quad \textbf{do} \begin{cases} i = i + 1; \\ c = c + X_t[i].weight; \end{cases} \\ newX_t.push\_back(X_t[i]); \end{cases}$

return $(newX_t)$

A last characteristic to be highlighted of the resampling step is that of all steps of the particle filter, the resampling step is the most difficult to be implemented in parallel since there is a relationship involving all the particles in time to make the selection of these. Then this can also be an important factor for the choice of the method for the resampling step, sometimes the preference of parallelization is greater than a preference for a more robust method of resampling.

3. Motion Model

This part of the work will discuss the model used to represent the state transition probability $p(x_t|u_t, x_{t-1})$ that is responsible to relocate the particles at every sampling time.

While the goal of this work is to create a full 6-DOF navigation system, here the estimation of the position was restricted to the horizontal plane, as the target vehicle isn't ready for field testing. A floating platform was used in its place so the state vector used in the 3-DOF navigation algorithm was Eq.(2).

$$x = \begin{pmatrix} x \\ y \\ \psi \end{pmatrix} \tag{2}$$

where x and y are the two dimensional planar coordinates and ψ is the angular orientation. As some places may contain ferromagnetic anomalies that may preclude the use of a compass, this work aims to use gyroscope for estimating the heading instead of a compass so that the navigation system could be used in such environments. Since the tests will be made in the horizontal plane, one gyroscope is sufficient to estimate the heading. To propagate the (x,y) position of the platform, was used an acoustic sensor that measures the speeds of the three main axes by using the Doppler effect, this sensor is called Doppler Velocity Log (DVL). Thus, in the motion model, two sensors are used, a DVL and a gyroscope.

Measurements of both linear and angular velocities were used as control actions and not as measurements in order to make the state vector small as possible and so decrease the number of particles needed to make the position estimation. So the motion model used in this work is a constant velocity kinematics model shown in equation Eq.(3).

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ z_{k+1} \end{bmatrix} = \begin{bmatrix} x_k + u * dt * cos(\psi_k) - v * dt * \sin(\psi_k) \\ y_k + u * dt * sin(\psi_k) + v * dt * \cos(\psi_k) \\ \psi_k + r * dt \end{bmatrix} \tag{3}$$

where x and y are the two dimensional planar coordinates, ψ is the angular orientation, u and v are the linear velocities in the x axis and y axis respectively , r is the angular velocity in the z axis and dt is the sampling period. To model the errors of the sensors used in this step was used the Gaussian distribution and in the validation tests of the navigation system of this work, they were sampled with a frequency of $5Hz$.

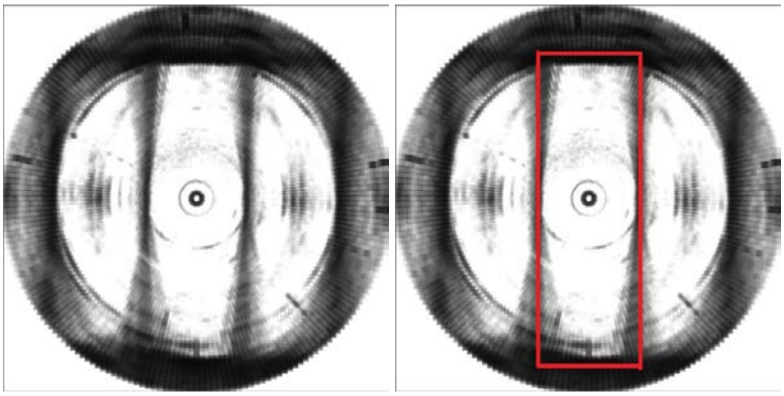

Figure 2. The left image show the raw image from the sonar and the right shows the contours of the tank

4. Measurement Model

This part of the work will discuss the model used to represent the measurement probability $p(z_t|x_t, m)$ that is responsible for assigning weights to the particles which in turn is the way that the measurements are incorporated in the estimation made by the filter. These weights are also used in the resampling step. The only sensor used in this step is a Mechanically Scanned Imaging Sonar (MSIS) (Ribas *et al.*, 2010).

The MSIS is a sonar which has only one transducer that generates a horizontal 2D acoustic image of the environment with a field of view of $360°$. It does so by rotating a transducer head at predefined angular increments that for each one of this increments it emits an acoustic beam to capture the obstacles in the environment in the respective direction. For each transmitted beam more than one return can be capture. Beside the distance, the sonar either capture the intensity of the echo of the obstacle.

This kind of sonar needs a lot of time to make an image of $360°$ of the environment. The factors directly related to the amount of time necessary to produce a complete scan are the beam discretization and the sampling interval of each one of this discretization. The reach that the sonar will have is determined by these two values. Therefore, one way to choose the period of the sonar scan is to choose values for the sonar range and for the beam discretization. Because of the dimensions of the tank where the tests were performed, (5 meters of width per 15.5 meters of length), the sonar reach was set to 10 meters and considering a reasonable discretization of the position of 10 centimeters, the beam discretization was set to 100. With this configuration the sonar stay with a scan time of 8,6 seconds.

In term of measurement model, with this kind of sonar it is possible to work in two different ways, one with its echoes intensity profiles and the other by processing its echoes intensity profiles to obtain range measurements to the nearest objects of the environment in each direction. In this work was chosen the distance approach and for this it is necessary to make a filtering on the echoes intensity profiles to eliminate the noises on it and thereby identify the contours of the environment. Figure 2 presents a full image of the test tank acquired from the imaging sonar.

Observing the Fig. 2 it is possible to identify the following sonar artifacts:

- There are several reflections of the walls of the tank that causes in the image false obstacles
- There are returns of objects that do not belong to the plane of the scan sonar, as the bottom of the tank, which although having a lower intensity, add confusion to the image.
- There is a severe amount of high frequency noise in the image, making it difficult to identify peaks of intensity in the return

So to achieve an approximation of the contour of the tank, it is necessary to find a filter that eliminates these noises. The choice of filters to be used has been restricted to linear filters so that the image was not distorted and so not to harm the position estimation. So to eliminate these noises were used a Gaussian filter (Nixon and Aguado, 2012), an echo killer and a threshold. The result of this filtering in the Fig. 2 is shown in Fig. 3.

Now that we have the range measurements from the MSIS it is possible to discuss the measurement model. The sonar model used in this work is based on the model proposed in (Thrun *et al.*, 2005) which try to model the physical behavior of the beam. In this model (Thrun *et al.*, 2005) considers four classes of errors, that is, local measurement noise, errors due to unexpected object, errors due to failures to detect objects and random unexplained noise. But due to the peculiarities of the Fig. 3, in this work in be considered only the error due to local measurement noise. This error models the fact that the sonar always measures the distance to the nearest object but with an error that can be modeled has a Gaussian.

Thus, the measurement model works as follows. For each particle a ray casting is executed, using the map of the environment, the position and the heading of the particle and the bearing of the sonar, to obtain the distance to the nearest

Figure 3. Result of filtering the sonar data

obstacle of the particle. With this distance, the distance obtained by the sonar and a stipulated sigma value, is calculated the probability $p(z_t|x_t^m, m)$ that by means of a Gaussian distribution representing the discrepancy between the two distances. This value represents the importance weight of the particle x_t^m.

A final aspect to be highlighted in the measurement model is that as the map of the environment has to be known a priori to be possible to execute the ray casting, it is possible to identify the particles, that due to the motion model, were beyond the bounds of the map and so assign a zero weight for these particles to they can be discarded in the resampling step as they represent inconsistent estimates.

5. Results

In this section is presented the results obtained from the navigation system proposed in this paper which was designed to estimate the horizontal position of a floating platform (the target vehicle is not yet ready for field testing) having knowledge of the environment map and using three sensors, a mechanically scanned sonar, a Doppler Velocity Log and a gyroscope.

Before showing the results is necessary to make some final comments. As mention in Section 2., to implement the particle filter it is necessary to know three probability density function, the initial state probability $p(x_0)$, the state transition probability $p(x_t|u_t, x_{t-1})$ and the measurement probability $p(z_t|x_t, m)$. The state probability $p(x_t|u_t, x_{t-1})$ and the measurement probability $p(z_t|x_t, m)$ were discussed in Section 3. and Section 4. respectively, then to close the explanation of the modeling system proposed in this work it is necessary to comment about the initial state probability $p(x_0)$. In the results obtained in this section, in the initialization of the particle filter was considered no a priori knowledge of the position of the platform in the tank and so the $p(x_0)$ was an uniformly distribution over the whole state space. Also to extract the estimated state in the results, from the set of particles of the filter, was used the formula shown in Eq.(4).

$$p(x_k|z_k, u_k) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \tag{4}$$

where x_k^i represents each particle, w_k^i represents the importance weight of each particle and N is the total number of particles.

As there was no other system that could track the position of the platform inside the tank to serve as a comparison for the results generated in this work, the way that will be made the validation of it will be by comparing the format of the trajectory carried by the platform. So the platform was manually displaced following a trajectory with known format and with the same initial and final points (within manual displacement accuracy) to validate the result. The format chosen was a rectangular because it is the same shape of the tank, where the test were conducted, and so the tank could be used as a reference. The tests were carried in a rectangular tank measuring 5 meters of width per 15,5 meters of length. Throughout the course, the heading of the platform was maintained at the same value.

The results that will be shown in this section were obtained using the sampling data from the tests performed in the tank cited above in an off-line processing (not in real time). As the processing was done in a off-line way, in this work was not a concern to determine an optimal number of particles wherein the filter functioned, the aim was to verify the operation of the filter. The results obtained from the navigation system proposed in this is shown in Fig. 4.

Figure 4 shows the trajectory obtained from the navigation system proposed in this work and also shows the trajectory obtained by pure integration of the velocities of the DVL using the heading obtained from a compass. Was chosen to use the trajectory obtained by integrating the noisy velocities of the DVL to have some basis for comparison. It also serves to show the improvement in the result on the estimation of the trajectory through the sensor fusion. The total time of the path was nine and a half minutes and to not confuse the analysis of the result, was taken out the part of the result of the navigation system proposed in this work where the filter has not yet converged.

Observing the Fig. 4 is possible to identify two aspects that show that the estimation of the position by the navigation

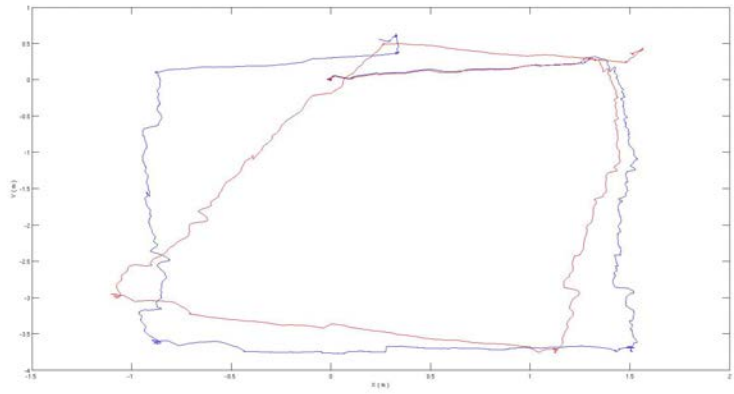

Figure 4. Comparison between the trajectory obtained by the navigation system proposed in this work (blue) and the trajectory obtained by integrating the velocities of the Doppler Velocity Log with the heading obtained from a compass (red)

system proposed in this work was accurate. The first aspect is related with the initial ($x = 0$ and $y = 0$) and final points of the trajectories. It can be observed from the Fig. 4 that the start and end points of the trajectory obtained by the navigation system proposed in this work are very close, as was to be expected by the way the test was done (considering a manual displacement accuracy). The second is related to the shape of the trajectories obtained. It can be observed from the Fig. 4 that the result obtained from the navigation system proposed in this work is shaped much like a rectangle as has two parallel sides vertically and two parallel sides horizontally, as was also to be expected. These results show that even with the restriction in the form of validating the system it was possible to verify certain accuracy. The trajectories obtained by integrating the velocities of the DVL has none of the two aspects discussed above.

To have a complete analysis of the operation of the navigation algorithm yet is necessary to verify the heading estimation. The navigation algorithm proposed in this paper uses a gyroscope to propagate the value of the heading and uses the sonar data to correct it indirectly. Thus to do this verification, the estimated heading obtained by a compass was used as a reference. The comparison between the results is shown in Fig. 5.

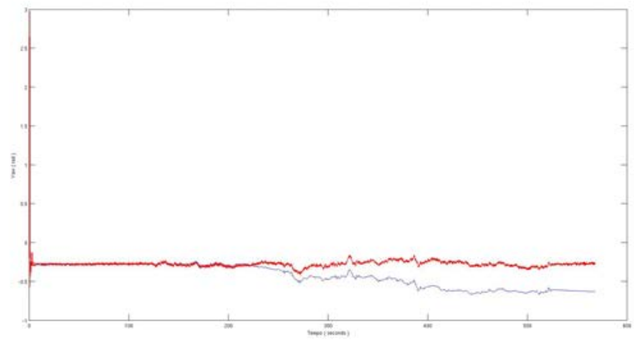

Figure 5. Comparison between the yaw obtained with the algorithm proposed in this work with the yaw obtained by a compass

Since, during the manual displacement of the platform on the trajectory rectangular, its heading was remained constant, Figure 5 shows that the result obtained by the navigation system proposed in this work is more consistent than that presented by the compass, this is because the estimate of the first one always varies around a mean value and the estimation of the second presents a drift. This drift presented in the estimation of the compass may have been caused by the influence of ferromagnetic material existing around the tank. This result shows why this work have opted to use a gyroscope instead of a compass since it is not guaranteed a good operation of the compass in certain places. Despite this drift of the compass can be seen that the estimates exhibit the same behavior. The result shown in Fig. 5 also demonstrates why the results obtained from the integration of DVL shown in Fig. 4 gave quite different than expected.

6. Conclusion and Future Steps

This paper presented a navigation system that estimate the horizontal position of a ROV in an underwater environment compound with man made structures using a mechanically scanned imaging sonar, a Doppler Velocity Log (DVL) and a gyroscope. As the sonar used in this work is a imaging sonar, in the measurement model, that has the sonar data as the only input, was necessary first to make a filter in its data to identify the contours of the environment and so get informations of distance. With these values of distance of the sonar and the priori knowledge of the map of the environment, a beam model was considered to model it. In the motion model was considered a 3 DOF constant velocity kinematics model using the DVL and the gyroscope. As these models are nonlinear, to make the fusion of the sensors was used the most common implementation of the particle filter that is the Sequential Importance Resampling (SIR).

The system was validated using real data and the results, that were obtained by off-line processing, shows that although it was not possible to compare it with an external system, could be proven some degree of accuracy of the trajectory obtained by the system as it was similar to the actual path that the platform was manually displaced.

Also as some environments of ROV applications may have ferromagnetic anomalies invalidating the use of a compass, a goal of the work was to achieve the estimated of the heading only based on a gyroscope. But to do this it is necessary to merge the gyroscope with others sensors since it is an inertial sensor, its estimated heading presents a drift. As the environment where the results were obtained presents ferromagnetic anomalies, the results showed the advantages of using the gyro integrated with the navigation system in place of a compass.

6.1 Future Steps

The next most important step to be done in the progress of the project is related to a better validation of the accuracy of the navigation system so an optic reference system is being installed on the test tank to provide an accurate external measurement of the platform trajectory to provide a quantitative measurement of the error of the proposed navigation system.

In this work was used a simplified model of the sonar, then as a next step will be studied a more elaborate model for the sonar to include more characterizes of it improving the position estimation. With the reference optical system, previously mentioned, will be possible to quantify the improvement in the estimation of the position with this changes in the model of the sonar.

Furthermore, as the results shown in this work have been generated by an off-line processing because the computational cost associated with the execution of the particulate filter, will be necessary to reconstructed the algorithm proposed in this work in an efficient parallel implementation to perform on-line real-time navigation.

And lastly as the target vehicle is approaching field-test readiness, the filter will be extended to provide full 6-DOF navigation.

7. ACKNOWLEDGEMENTS

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