TOWARDS A DVL-BASED NAVIGATION SYSTEM FOR AN UNDERWATER ROBOT

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Abstract

This paper represents a first step towards a navigation system based on a ARGONAUT[TM] DVL (Doppler Velocity Log) sensor for an underwater remotely operated vehicle (ROV). The sensor measures the water currents, the vehicle ground speed, the altitude, the depth and its attitude. The navigation system is formulated in a way that is able to deal with the future integration of new sensors like a DGPS. Hence, sensor fusion and filtering techniques are used to get a position estimate using data from all sensors. One of the widely applied strategies is the Kalman filter. In this paper an EKF-based navigation system using a DVL sensor and the non-linear dynamic model of an underwater robot is proposed, implemented and evaluated through simulation.

1 Introduction

The navigation system is responsible for the location (position & orientation) of the vehicle in the environment relative to some fixed coordinate system. Its performance is essential for the ROV or AUV (Autonomous Underwater Vehicle) in order to be able to maneuver between waypoints as well as to return to specific locations within the environment without becoming lost. For surface navigation, DGPS is the widely used method. Nevertheless, it is well known that DGPS cannot be used under the water. In order to get absolute position measurements, it is possible to use acoustic transponder networks like LBL (Long Base Line) , SBL (Short Base Line) or USBL (Ultra Short Base Line). LBL is based on the use of at least 3 anchored transponders periodically interrogated by the robot, which computes the range to each transponder by measuring the times of flight. Then a triangulation process allow to compute the absolute position. The drawback of LBL, is due to the need of deploying, previously to operation, the transponders as well as the calibration process that has to be carried out. Modern systems, like GIB (GPS Intelligent Buoys), work as an inverted LBL system which use surface buoys equipped with DGPS incorporating a self-calibration procedure. The SBL and USBL simplifies the operational procedure. In the first, two transducers are mounted on the ship's hull as far apart as possible. For the second, only one transducer is needed, hence, the system becomes more portable and flexible. Although USBL and SBL systems do not require additional equipment to be deployed in the water or on the seafloor, they do require careful shipboard calibration. Although those systems are currently available, there still expensive for very low cost

ROVs like the one we are dealing with, GARBI (see fig.1). Cheaper navigation systems are commonly based on the integration of several low cost sensors, like for instance a DVL for estimating the 3D velocity vector, an INS (Inertial Navigation System) for estimating the attitude (commonly accelerations are not used for low speed vehicles), and a depth sensor (commonly a pressure or an acoustic sonar sensor). For a better description of the systems described above, refer to (Blidberg et al. 1995) and the references therein.

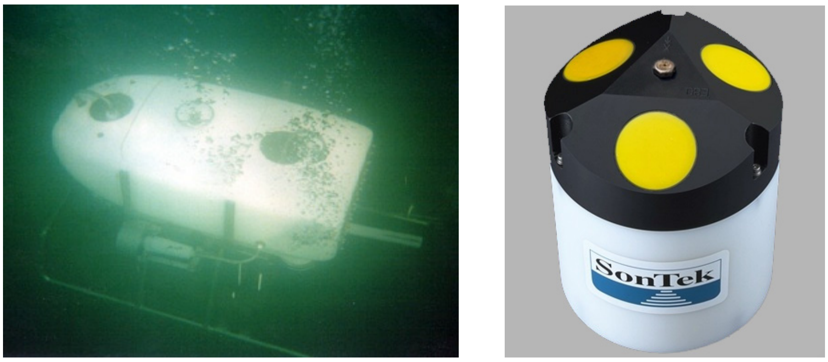
In this paper we present a simple navigation system based on the ARGONAT™ DVL sensor which includes measurements of ground speed, heading, altitude and depth. All the measurements are integrated through an EKF (Extended Kalman Filter) which makes use of the non-linear dynamic model of the GARBI ROV. The paper is organized as follows. First, GARBI ROV and the ARGONAT™ DVL sensor are described in sections 2 and 3. The dynamic model of the robot is briefly presented in section 4. Next section presents the main aspects of the proposed extended Kalman Filter. Section 6 presents the design of experiments and section 7 reports their results. Finally, the conclusions are presented in the last section.

2 GARBI ROV

GARBI (Amat et al. 1996), see fig. 1a, was designed with the aim of building an underwater vehicle using low cost materials, such as fiber-glass and epoxy resins. To solve the problem of resistance to underwater pressure, the vehicle is servo pressurized with a compressed air bottle. The vehicle has 4 thrusters, two for horizontal movements (axis x, T1 and T2) and two for vertical movements (axis z, T3 and T4). Due to the distribution of the weights, the vehicle is completely stable. *Pitch* and *roll* angles are insignificant. For this reason the vertical and horizontal movements are totally independent. The number of controlled DOF is 3: *heave*, *yaw* and *surge*. The vehicle had several sensors: 2 compasses, 2 pressure sensors and 2 water speed sensors, but after the current reconstruction its navigation system will be principally based in an ARGONAUT™ DVL sensor and a DGPS. GARBI's Dimensions are: length 1.3 m., height 0.9 m and width 0.7 m. Maximum speed is 0.5 knots.

3 The ARGONAUT™ DVL sensor

The SonTek/YSI Argonaut™-DVL (Doppler Velocity Log) is a versatile sensor which measures the water currents, the vehicle speed over the sea floor, and the altitude. In addition, the system includes in the same package other sensors able to provide measurements of pressure (depth), water temperature, and attitude. The Argonaut™ DVL was developed primarily for the underwater vehicle industry because of their requirements for compact, versatile, and affordable components capable of withstanding full-ocean depths. The DVL's compact size, low power draw (<0.5W) and 600 m pressure rating make it the ideal instrument for experimental underwater vehicles. It is worth noting that as a speed sensor, the Argonaut™ DVL measures its speed relative to a user-programmable cell layer that is located far away from the vehicle. This feature allows the sensor to measure ocean current or vehicle speed away from the contamination caused by the vehicle itself. This is a key advantage of using an Argonaut™ Doppler instrument instead of electromagnetic or mechanical current meters. Furthermore, the Argonaut™ DVL does not require calibration or other significant maintenance, which keeps the long-term operational costs to a minimum.



(a) (b)

Figure 1. (a) the GARBI ROV (b) ARGONAUT™ DVL.

4 Model of an underwater vehicle

As described in the literature (Fossen 1994) the non-linear hydrodynamic equation of motion of an underwater vehicle with 6 DOF, in the body fixed frame, can be conveniently expressed as[1]:

$$
\begin{aligned}
&{}^{B}\tau + G(\eta) - D\left({}^{B}\upsilon\right){}^{B}\upsilon + \tau_p = \\
&\left({}^{B}M_{RB} + M_A\right)\cdot {}^{B}\dot{\upsilon} + \left({}^{B}C_{RB}({}^{B}\upsilon) + C_A\left({}^{B}\upsilon\right)\right)\cdot {}^{B}\upsilon
\end{aligned}
\tag{1}
$$

Through the manipulation of eq. (1) the robot acceleration can be computed. Velocity can be obtained through integration, and the position rate of change can be computed through the following kinematic transformation:

$$
{}^{E}\dot{\eta} = J\left(\eta\right)\cdot {}^{B}\,\upsilon \tag{2}
$$

For GARBI ROV, the model can be simplified since it is stable in *pitch* and *roll*, so it can be formulated in 4 degrees of freedom. Section 5.2 shows the discrete-time model used for the experiments. The dynamic parameters needed in eq. (9), where previously identified through experimentation. Refer to (Ridao et al. 2001) for details about how the model was identified.

5 Extended Kalman filter

Due to the non-linear behavior of the dynamic model of an ROV, an extended Kalman filter has been considered as a convenient method to formulate the navigation problem (Grober & Hwang 1983).

$$
\hat{x}_k^- = f(\hat{x}_{x-1}, u_k, 0) \tag{3}
$$

$$
P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \tag{4}
$$

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[1] All the equations shown here follow the standard nomenclature proposed in (Fossen 1994)

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + V_k R_k V_k^T)^{-1} \tag{5}$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-, 0)) \tag{6}$$

$$P_k = (I - K_k H_k) P_k^- \tag{7}$$

The fig. 2 shows the block diagram of the proposed navigation system. The output of the DVL system (the velocity, the depth and the orientation), is used as the measurement update for the EKF. The other input to the filter is the control input *u,* which is the vector of the generalized force (force and torque) applied by the propellers.

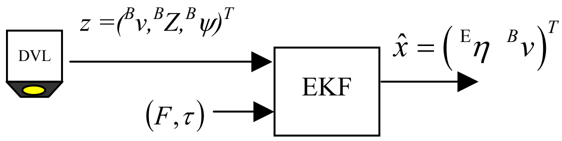

Figure 2. Block diagram of the proposed navigation system.

In the following sections, the main components of the filter are presented.

5.1 State vector

To implement the filter the following state variables have been chosen:

$$x = \begin{pmatrix} x & y & z & \psi & u & v & w & r \end{pmatrix}^T \tag{8}$$

The first 4 components are the 3D position and the heading of the vehicle, while the last 4 components are the linear velocity vector and the angular speed.

5.2 Discrete time model

Adapting the eq. (1) and (2), and simplifying the model to 4 degrees of freedom the discrete time model shown in eq. (9) is obtained. The s vector is considered a model perturbation and represents the process noise.

$$\begin{pmatrix} x \\ y \\ z \\ \psi \\ u \\ v \\ w \\ r \end{pmatrix}_{k+1} = \begin{pmatrix} x + (\cos(\psi)\cdot u - \sin(\psi)\cdot v)\cdot dt \\ y + (\sin(\psi)\cdot u + \cos(\psi)\cdot v)\cdot dt \\ z + w \cdot dt \\ \psi + r \cdot dt \\ u + \left(\dfrac{\mathrm{X} + (m - y_{\dot v})\cdot v \cdot r - (x_u + x_{u|u|}\cdot |u|)\cdot u + \delta_u}{(m - x_{\dot u})} \right)\cdot dt \\ v + \left(\dfrac{\mathrm{Y} + (m - x_{\dot u})\cdot u \cdot r - (y_v + y_{v|v|}\cdot |v|)\cdot v + \delta_v}{(m - y_{\dot u})} \right)\cdot dt \\ w + \left(\dfrac{\mathrm{Z} - z_w \cdot w + \delta_w}{(m - z_{\dot w})} \right)\cdot dt \\ r + \left(\dfrac{\mathrm{N} - (n_r + n_{r|r|}\cdot |r|)\cdot r - ((m - y_{\dot v}) - (m - y_{\dot u}))\cdot v \cdot u + \delta_r}{(m - n_{\dot r})} \right)\cdot dt \end{pmatrix}_k + \begin{pmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \\ s_8 \end{pmatrix}_k \tag{9}$$

5.3 Matrices of the filter

To complete the filter it is also necessary to determine the following matrices:

- **A**: the Jacobian matrix of partial derivatives of the model with respect to the state vector.
- **W**: the Jacobian matrix of partial derivatives of the model with respect to the noise vector.
- **H**: the Jacobian matrix of partial derivatives of the sensor model with respect to the state vector.
- **V**: the Jacobian matrix of partial derivatives of the sensor model with respect to the noise vector.
- **Q**: the covariance matrix of process noise.
- **R**: the covariance matrix of measurement noise.

All the previous matrices are not reproduced here due to space limitations.

$$H = diag(0 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0) \qquad H = 0_{8x8} \tag{10}$$

The **H** matrix can take two different values, see eq. (10). The first value is used to merge the measures from the DVL sensor with the estimate of the model. Note that the sensor provides information about velocities in the three axis, depth and yaw orientation. The second configuration of **H** isolates the model estimation, or what is the same, no measurement update is taken into account to correct the prediction of the model. This value of the H matrix could be used to disconnect a damaged sensor, or to provide estimations within two measurements.

$$Q = diag\left(\sigma_X^2 \quad \sigma_Y^2 \quad \sigma_Z^2 \quad \sigma_\psi^2 \quad \sigma_u^2 \quad \sigma_v^2 \quad \sigma_w^2 \quad \sigma_r^2\right) \tag{11}$$

$$R = diag\left(\sigma_{z_1}^2 \quad \sigma_{z_2}^2 \quad \sigma_{z_3}^2 \quad \sigma_{z_4}^2 \quad \sigma_{z_5}^2 \quad \sigma_{z_6}^2 \quad \sigma_{z_7}^2 \quad \sigma_{z_8}^2\right) \tag{12}$$

Q and **R** are covariance matrices which describe the process and measurement noises, both are considered diagonal to simplify the tuning of the filter. The values in the diagonal are the noise variances affecting the corresponding state variables. This values were selected experimentally.

6 Experiment design

The proposed navigation system was implemented using MATLAB scripts. The block diagram corresponding to the simulation system is shown in fig. 3. The input to the system is the generalized force vector (force and torque). Using this force as input, the dynamic model of the robot, together with a source of Gaussian unbiased noise acting as process noise, were used to simulate the trajectory followed by the robot. In the following paragraphs we will refer to this trajectory as the "real" trajectory. A new source of noise, the sensor noise, was added to the real trajectory to simulate the measurements provided by the sensor. Finally the force, as well as the measured trajectory, are used as the control input and the measurement update for the filter. Since the sensor frequency is 6 Hz, and the navigation system is expected to work at 10 Hz, the filters iterates at 10 Hz. The switch shown in the corresponding block of fig. 3 allows the filter to work exclusively predicting or predicting and updating. The switch was implemented, by selecting the correct H matrix (eq.10).

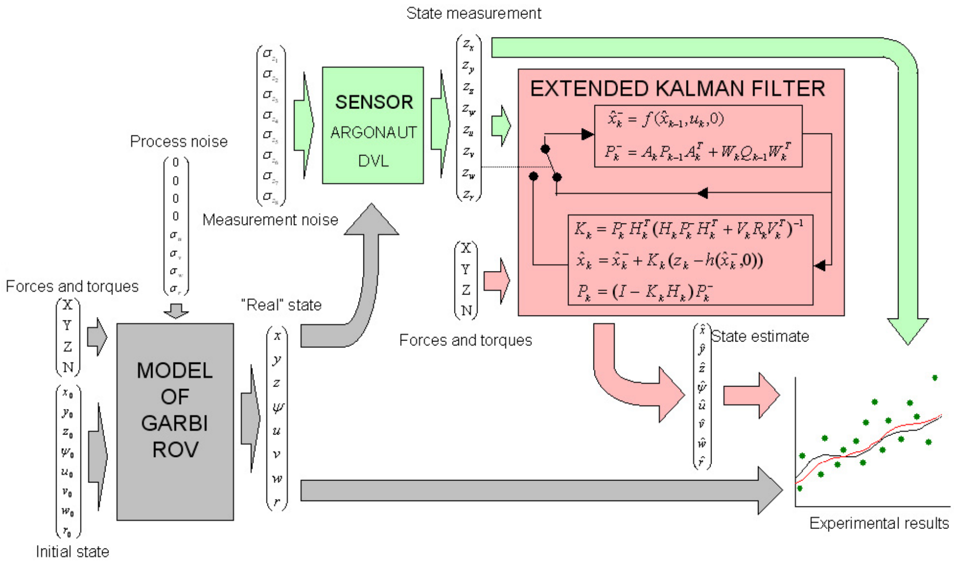

Figure 3. Block diagram of the proposed experiments.

7 Results

The main goal to achieve in the experimental phase was to obtain a good set of tuning parameters (values for the covariance matrices Q and R) which assure a near optimal behavior of the filter. Hence a set of experiments were undertaken to find the values which minimizes the difference between the estimated and the "real" trajectory.

Due to the *pitch* and *roll* stability *heave* is not coupled with any other DOF. Although *yaw* is coupled with *surge* and *sway*, for GARBI ROV this coupling is almost negligible. Hence, for both DOF uncoupled experiments were carried out at different speeds to tune the filter. On the other hand *surge* and *sway* DOFs are highly coupled depending also on the *yaw* DOF. Therefore, the filter parameters related to both DOF were simultaneously selected using the same set of trials. The experiments consisted on exciting the robot first in *surge* DOF, then in *yaw* DOF and finally in *surge* and *yaw* DOFs simultaneously.

After the experiments were completed a set of values for the matrices Q and R were determined. The experimental results and the experience acquired about the filter behavior was used to choose the final values (see eq. (13) and (14)).

$$Q = diag\begin{pmatrix}0.01 & 0.01 & 0.01 & 0.01 & 9\cdot10^{-5} & 1\cdot10^{-5} & 8\cdot10^{-5} & 3\cdot10^{-4}\end{pmatrix} \quad (13)$$

$$R = diag\begin{pmatrix}0 & 0 & 0.04^2 & 0.04^2 & 0.04^2 & 0.04^2 & 0.04^2 & 0\end{pmatrix} \quad (14)$$

In order to test the whole navigation system, a final experiment was carried out. In this case the robot was controlled to follow a spiral shaped trajectory where all the DOFs were implied in the movement

Fig 4 shows the 3D trajectory followed by the robot. Note that the filtered trajectory matches quite well the “real” trajectory, reducing the noise present in the measurements by the means of the information given by the model.

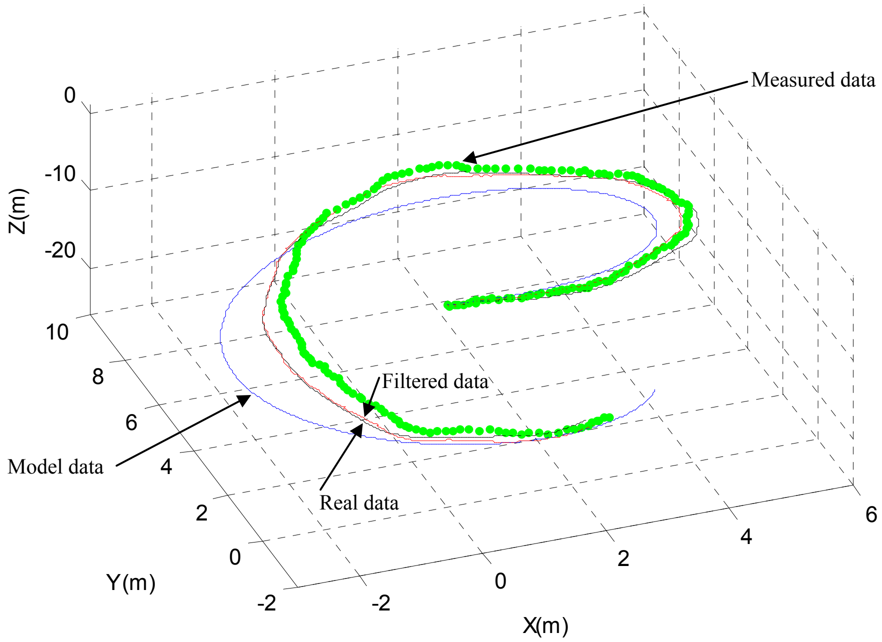

Figure 4. Spiral trajectory.

Fig 5 shows the velocity plots for each DOF. As it can be seen, the measurement noise is practically eliminated. The filtered signal follows the trend of the “real” velocity and no delay is observed.

8 Conclusions

In this paper we have presented a first step towards a DVL based navigation system. The system uses velocity, heading and depth measurements as the updates for an extended Kalman filter which makes use of the dynamic model of GARBI ROV. The system has been implemented and tested on simulation with satisfactory results. Next step will be the inclusion of DGPS fixes, when the robot is on surface. Further work will consist on the implementation and testing on GARBI ROV.

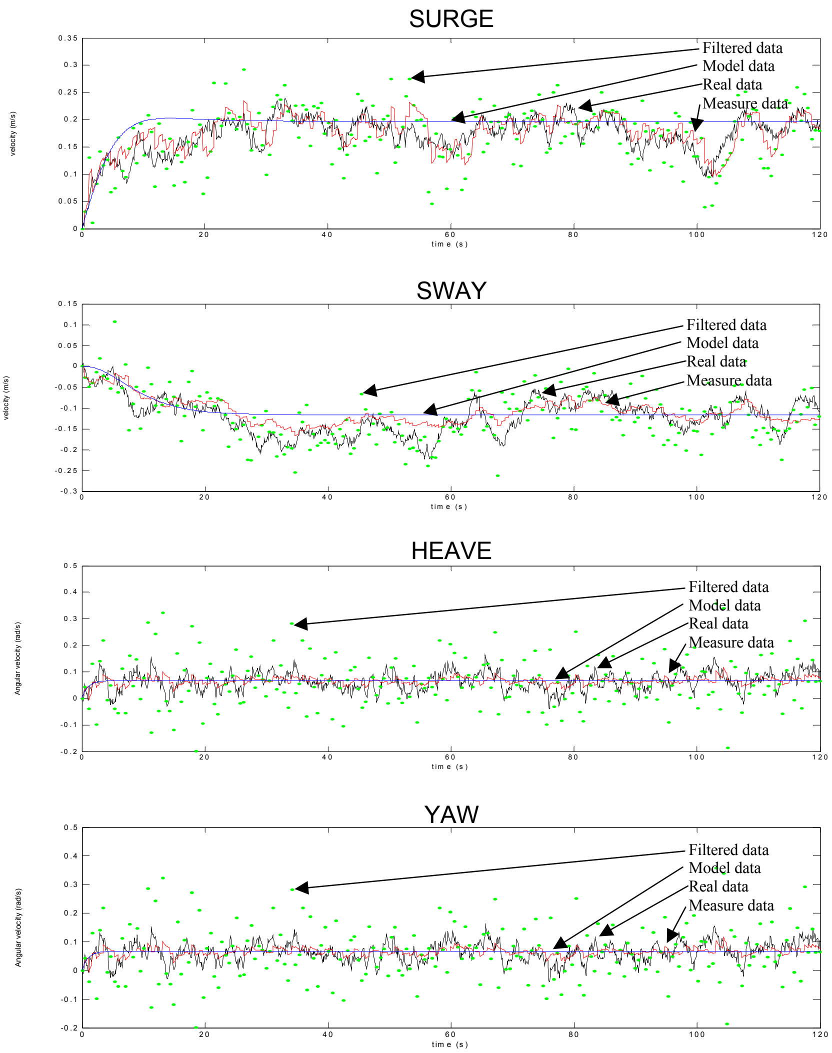

Figure 5. Velocity plots for a spiral trajectory.

References

Amat, J., Batlle J., Casals A. and Forest J. (1996). *GARBI: a low cost ROV, constrains and solutions*. In: 6ème Seminaire IARP en robotique sous-marine. pp. 1-22, Toulon-La Seyne, France.

Ridao, P., Batlle, J., and Carreras, M., (2001) Model Identification Of A Low-Speed Uuv With On-Board Sensors. Control Applications in Marine Systems CAMS'01, Scotland (UK).

Fossen, T.I. (1994). *Guidance and Control of Ocean Vehicles*, John Wiley and Sons, New York, USA.

Grober R. and Hwang P. Y. C., (1983). *Introduction to Random Signals and Applied Kalman Filtering*. John Wiley and Sons. New York, USA.

Blidberg D.R, Jalbert J. C. (1995) .Chapter 7. Mission & System Sensors. Underwater Robotic Vehicles. Design and Control. Ed. J. Yuh, TSI press, pp.185-220. Alburquerque, New Mexico USA.