Implementation of a ROV Navigation System Using Acoustic/Doppler Sensors and Kalman Filtering

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***Abstract*- Hydro-Quebec developed a new underwater ROV which is use to inspect its dams. Since 2000, the ROV has allowed Hydro-Québec to save 5M$ in inspection cost. This paper presents the study of a Kalman filter and its performances. Kalman filtering is used to merge data from fiber gyros, DVL, accelerometers and global positioning system in order to have a better estimation of the position and orientation of the ROV. In real systems, sensors do not send data at the same rate and data acquisition is often intermittent. One innovative aspect of this approach is that it accepts asynchronous information and delay from the sensors. Experimental results in real environment are presented**

I. Introduction

As a part of the Hydro-Québec dam security program, an underwater remotely operated vehicle (ROV) has been under development for the past few years at the Institut de recherche d'Hydro-Québec (IREQ). Such a ROV may be used in various inspection tasks taking place in underwater environments. The main purpose of this vehicle is the inspection of dam surfaces. Over the years, the deterioration of the dam concrete and other immerged elements needs to be repaired. Inspection is done to prepare reabilitation work.

As the ROV inspects the dam, cracks or defects on the surface are identified using the on-board camera, precisely located and are reproduced in a virtual environment. The virtual environment consists of a complete scaled graphical model of the dam [1] and the graphical and dynamical model of the submarine. Later on, maintenance crews will return to the identified defects to follow their evolution in time or to perform restoration work. To perform such tasks, the ROV must be equipped with a precise navigation system, giving at all time its exact position relative to the dam.

The ROV navigation system consists of two parts: a variety of sensors giving information on the vehicle's position and movement, and a navigation algorithm. Navigation systems commonly use multiple sensors. Often, the information received from the various sensors is redundant. Redundancy can be use to improve the position estimate and overcome sensor failure. The sensors that compose the navigation system are exposed in section II. The navigation algorithm takes input from the different sensors and evaluates the best possible estimate of the vehicle's position. The navigation algorithm is based on Kalman filtering techniques. More specifically, the filter merges the position information obtained by an acoustic positioning system and the velocities obtained from a Doppler sensors system. Prior work on navigation systems that uses Doppler and accoustic sensors can be found in [5] and [6]. Many strategies in the Kalman filtering process has been suggested before for the purpose of sensor failure accommodation [2] or adaptive Kalman filtering [3]. In real systems, sensors do not always send data at the fixed rate and data acquisition is often intermittent. So additional developments take place to deal with asynchronous data delivery and delays in measurements. A delay in a measurement is the time between the moment that the measurement is valid and the moment that it is available to the navigation system. Furthermore, the algorithm is designed to accept various rates of data from the sensors. It also includes a filter switching process so that only the valid data is used for the position estimate.

The paper is organized as follow. Section II contains a brief description of the navigation sensors. Section III describes the basic Kalman filter, which is widely used in sensor fusion and the shortcomings of this first design. Section IV presents an improved Kalman filter fusion strategy. Section V presents simulations results. Section VI contains some experimental data available at this time and extracts the similarities with the simulation results.

II. Navigation Instrumentation

The navigation system of the Hydro-Québec submarine is composed of the following systems and sensors.

Inertial system. This system, called DQI, provides position, linear velocities and accelerations, orientation and angular velocities. However, in this work, only the orientation and angular velocities are used.
Acoustic system. This system provides the XYZ position of a sonar transducer mounted on the submarine. Only the XY coordinates are used.
Bathymeter. This sensor gives the Z coordinate and is combined with the XY coordinates of the acoustic system to compose the absolute position measurement. We get the Z coordinate from the bathymeter instead than from the acoustic system because it is much more accurate and reliable.

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Doppler system. This system, commonly identified as DVL, provides the XYZ linear velocities of the submarine.

Instrument	Variable	Update rate	Precision	Range	Variance
DVL	XYZ Velocity	6Hz	±0.2% ±1mm/s	0.5-30m	0.00009
Acoustic positioning system	XY Position	0.5Hz	±0.5m	500 m	0.02777
Bathymeter	Z Position	5Hz	±1 cm	full	0.000013

Table 1 Navigation sensors characteristics

III. Simple Kalman Filter

The Kalman filter, well covered elsewhere [4], is an optimal linear estimator based on an iterative and recursive process. It is used in a wide variety of applications, and applies particularly well to sensor fusion. It recursively evaluates an optimal estimate of the state of a system. Typically, the vector describing the state of a vehicle evolving in a 3D space can be expressed as:

$$\mathrm{X}=\left[x \quad y \quad z \quad \dot{x} \quad \dot{y} \quad \dot{z} \quad \alpha \quad \beta \quad \gamma \quad \Omega_x \quad \Omega_y \quad \Omega_z\right]'$$

Where

$x \ y \ z$ are the position coordinates of the vehicle
$\dot{x} \ \dot{y} \ \dot{z}$ are the corresponding velocities
$\alpha \ \beta \ \gamma$ are the Euler angles describing the orientation of the vehicle and
$\Omega_x \ \Omega_y \ \Omega_z$ are the angular velocities.
Actually, the Kalman filter under development applies only to the position so let's redefine the vector X as:

$$\mathrm{X}=\left[x \quad y \quad z \quad \dot{x} \quad \dot{y} \quad \dot{z}\right]'$$

The filter produces a new estimate of the position when one of the following situations occurs. If a new position measurement from the acoustic system is available, then it computes the new estimate with this new information (measurement update process). If there is no new information available before a fixed amount of time *dt,* then it updates the position based on previous information of position and speed (time update process).

A. Time Update Process

As described by Eq. 1 and Eq. 2, the optimal estimate from the previous iteration, noted *X(k-1)* is projected in time through the state transition matrix *A*, and the noisy inputs *U(k)* (indirect sensors) are fed to the system through matrix *B*, relating the inputs to the state.

$$P_{priori} = A \cdot P \cdot A' + Q \qquad (1)$$

$$X(k) = A \cdot X(k-1) + B \cdot U(k) \qquad (2)$$

To illustrate, we take as an example our ROV navigation system. In Eq. 1, the state *X* is the linear position of the vehicle and *U* is the input from a linear velocity sensor. Matrices *A* and *B* reflect the kinematic of the system. Eq. 2 projects in time the error covariance matrix *P*, representing the variance of the error on the estimate *X*. *Q* is the covariance matrix associated with the process noise from the measurements *U(k)*.

B. Measurement Update Process

This process is formalized by Eq. 3 to 5, in which direct noisy state measurements *Z(k)* coming from sensors are compared with the prior state estimate $X(k_{past})$, yielding a correction to apply to this prior estimate to obtain the new estimate *X(k)*. Matrix *H* relates the measurements to the state.

$$K = P_{priori} \cdot H' \cdot (H \cdot P_{priori} \cdot H' + R)^{-1} \qquad (3)$$

$$X_{corrigé}(k_{past}) = X(k_{past}) + K \cdot (Z - H \cdot X(k_{past})) \qquad (4)$$

$$P = (I - K \cdot H) \cdot P_{priori} \qquad (5)$$

The importance of each estimation (the prior estimate $X(k_{past})$ and the measurement *Z(k)*) is determined by the Kalman gain *K*. This gain is in turn determined by matrices *Q* and *R*, which respectively represent the process noise covariance (indirect measurements) and the measurement noise covariance (direct measurements). The Kalman gain *K* takes a value between 0 and 1, 0 representing the use of the indirect measurements only, 1 the direct measurements only. The error covariance matrix *P*, modified in Eq. 2, is again corrected in Eq. 5 to reflect the measurement update process. Continuing with the previous example, *Z(k)* in Eq. 4 represents a measurement coming from a position sensor and *H* is equal to [1 0] since there is direct correspondence between *Z* and *X*.

C. Strengths and Weaknesses of the Simple Kalman Filter

The noise from the DVL is accumulated over every iteration because the velocity is integrated to obtain the position. This results in a diverging position error and therefore this sensor alone becomes unusable over long periods of time as seen in Fig. 1. The position error of a typical direct position sensor, such as the acoustic positioning system is important. These systems are subject to intermittence and have larger noise levels over short periods of time. However, their position estimates do not drift over time. The error is close to zero-mean, which makes them more reliable on the long run. The position estimate obtained from the Kalman filter combining both of these sensors has been simulated. The results of the simulation are plotted in Fig. 1. As one can see, this combination takes advantages from both of these sensors: The absence of drift from the position sensor and the smoothness of the DVL data.

However, this basic Kalman filter design does not satisfy the precision needed by the application. First, the position obtained from the acoustic system is not valid at the time it becomes available, but at a certain amount of time before. Second, if a sensor fault occurs, it must be detected and the filter should not incorporates the data from this system in a new estimate. Finally, the update rate of the sensors may vary. For example, if the vehicle is far from the transponder beacons, the measure will take more time to be done because the acoustic signal has to travel the distance in the water for each beacon.

IV. Implementation Aspect

A. Transformations Applied to the Data Before Filtering.
Data from particular sensors require some transformations before being sent to the Kalman filters. The kinematics model of the submarine describes its movement relative to an inertial frame called *fixed*. For convenience, the dynamics equations of the submarine are developed relative to its centre of mass. A reference frame identified as *local* is attached to the centre of mass and its orientation correspond to the principal axis of inertia. Therefore, the position and speed obtained from the sensors has to be transformed to describe the position and speed of the *local* frame relative to the *fixed* frame expressed in the *fixed* frame.

The position obtained from the acoustic system is transformed as follow:

The speed obtained from the DVL system is transformed as follow:

$$\begin{aligned}\left[{}^{FIXE}V_{LOC}\right]_{FIXE} &= ROT\{FIXE,DVL\}\left[{}^{FIXE}V_{DVL}\right]_{DVL} \\ &-\left[{}^{FIXE}\Omega_{LOC}\right]_{FIXE} \wedge \left(ROT\{FIXE,LOC\}\left[{}^{LOC}P_{DVL}\right]_{LOC}\right)\end{aligned} \quad (6)$$

Where:

$ROT\{FIXE \quad DVL\}$ is the rotation matrix describing the orientation of the DVL system relative to the fixed frame.

$\left[{}^{FIXE}V_{DVL}\right]_{DVL}$ is obtained from the DVL system.
$\left[{}^{FIXE}\Omega_{LOC}\right]_{FIXE}$ is the angular velocity of the local frame obtained from the gyros.
$\left[{}^{LOC}P_{DVL}\right]_{LOC}$ is the position vector of the DVL system relative to the *local* frame expressed in the *local* frame.

B. Asynchronous Filtering
Sensors data are available at different and changing rates from the various sensors. The sensor fusion algorithm accepts asynchronous signals by switching to the appropriate estimation procedure depending on which signal is provided. For instance, the DVL provides data at a rate approximately 12 times higher than that of the acoustic position sensor. When both sensors provide new data, the Kalman filter model is used. However, 11 times out of 12 only the DVL provides new data, and so a simple integration is used to perform the position update.

C. Delay Compensation for the Acoustic Data
A time stamp is recorded when a position data is produced by the acoustic system. The value of the time stamp is the actual time less a calibrated delay. This time stamp is associated with the position data.

The position estimate between two acoustic position data are kept in memory. When the new position data from the acoustic system is available, the algorithm performs the correction on the position estimate recorded in the buffer at the time indicated by the time stamp associated with this new data. Then the position updates, based on the DVL data, are performed from this time to the actual time. In other worlds, the position update $X(k_{past})$ of Eq. 4 is replaced by the new position estimate and then the position is updated by integrating the velocity data from this new position estimate in the past to the actual time using Eq.2. This integration phase continues until a new acoustic position becomes available.

V Simulation result

The data are generated with the dynamic model of the submarine and its controller. The position of the model is identified as *Virtual_submarine.* A white noise with variance obtained from experimentations (see table 1) is added to the *Virtual_submarine* positions in order to generate the acoustic data. The DVL data are obtained from the velocities of the model. The acoustic data is identified as *V_Positioning_system* and the DVL data is identify as *DVL_only* while the position estimate is identified as *Xkalman*.

The results of first simulation (Fig. 1) show the fusion of the data from the acoustic system and the DVL system by the basic Kalman filter first designed. The submarine starts at position zero then reaches the first target at –2 m. At time t = 500s, the submarine reaches the position target 0 m and returns to the –2m target at time t= 1000s. The goal of this simulation is to validate the adequate execution of the Kalman filter. The acoustic data are not shown in this graph for clarity. The position drift for the DVL is very slow and the error becomes significant only after one hour of simulation. The data plotted on this graph represents 30 minutes of simulation starting after four hours of simulation.

As anticipated, the filter is doing a good job. However, the acoustic signal is generated instantaneously (without delay), there are no calibration errors on any systems and no sensor failures in this simulation.

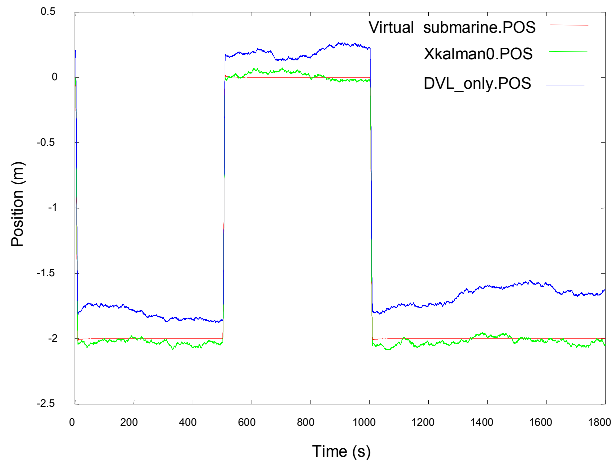

Fig.1 Kalman filter compensation for the position drift of the DVL.

The next simulation is intended to show the impact of the acoustic system delay and DVL system failures. Suppose that a reasonable delay for the acoustic system is 5 s. Also, in order to amplify the impact of the acoustic data on the position estimate, let the variance related to the acoustic system be 0.002. During the first 10 s, the effect of the delay is that the *Xkalman0.POS_X* curve is behind the *Virtual_sumbmarine.POS_X* curve. The DVL failure occurs at 11s where the *Xkalman0.DVL_actif* curve changes from level one to level zero and become active again at 12 s. During the failure time, the filter considers the DVL input as zero value. Acoustic measurement delays and DVL failure are inherent to this navigation system. At 20 s after the beginning of the simulation, the accumulated error of the delay and DVL failure is approximately 20 cm.

The next simulation shows the corrections made for the delay and for the DVL failure. The description of the correction applied for the delay is given in the previous section. The correction applied in the case of the DVL failure is very simple in this algorithm and it works fine for small period of time. The algorithm keeps the last valid velocity and performs the time update procedure with it. Then this valid velocity is reduced for a certain percentage and the result becomes the new valid velocity for the next time update. For a longer period of time, the algorithm stops to perform the time update procedure and the controller changes from automatic to manual mode.

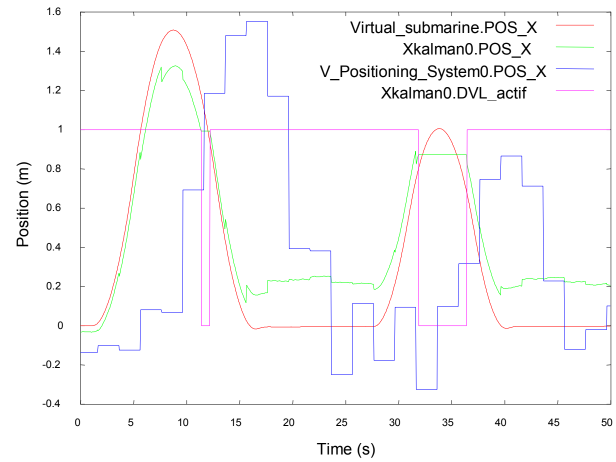

Fig.2 Impact on position estimate of the acoustic position delay and DVL failures.

During the first 10 s of the simulation, the position estimate curve follows the position curve of the model. This represents an improvement compare to the previous simulation. The first DVL failure occurs at 11 s. While there is still a deviation of the position estimate relative to the position of the vehicle, the position error generated by the DVL failure is small compared to the one obtained in the previous simulation. At 20 s after the beginning of the simulation, the accumulated error of the delay and DVL failure is less than 5 cm. On the other hand, for a DVL failure lasting for more than 5 s, as the one starting at 25 s, the use of the last valid velocity generates an important error because the vehicle changes its velocity direction during the failure. However, as the time pass, the position estimate curve is coming closer by small steps to the vehicle position curve under the influence of the acoustic position system while the vehicle is at rest.

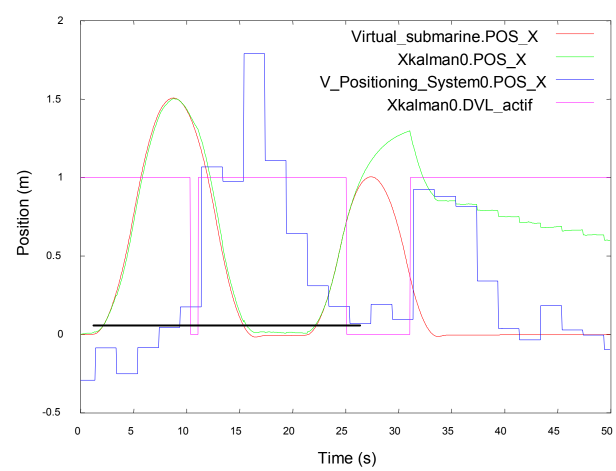

Fig.3 Position estimate corrected for the acoustic position delay and DVL failures.

The velocity obtained by the DVL system is the linear velocity of one particular point on the vehicle. The transformation applied to the velocities depends on the angular velocities and the XYZ coordinates of the centre of the DVL system relative to the local frame. This transformation is necessary and the calibration should be done accurately. In the next simulation, the DVL is located at (-25 cm, 0, 25 cm) relative to the local frame. However, an error of 5 cm relative to the X and Z axis is made so this transformation considers the DVL system located at (-20 cm, 0, -20 cm). The position drift is dependant on the angular displacement and it can be observed from Fig. 4 that a small error in the DVL position generates considerable error on the vehicle's position.

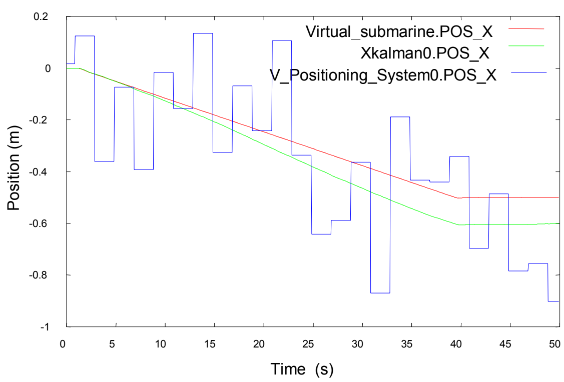

Fig.4 Calibration errors effect on the position of the DVL system

VI Experimental results

The experiments were conducted with the ROV III of Hydro-Québec at the old port of Montreal. Unfortunately, due to a technical problem, only a part of the experiments planned for this session has been performed. The acoustic system has not been in operation for these experiments. However, the bathymeter is used for the Z coordinate replacing the acoustic system used for the X coordinate in simulation. Though, the interest is more on the observation of the behaviour described in the previous section than on the reproduction of the simulation results. In the following figures, the absolute sensor is the bathymeter and the corresponding curve is identified as *Bathymeter0.POS_Z.* The bathymeter sensor is accurate and it can be considered as a reference to establish a point of comparison with the curve obtained from the Kalman filter. The position curve obtained by simple integration of the DVL data is not plotted. However, the DVL data are the only data used in the filter so the curved *Xkalman0.POS_Z* represents the position obtained by the DVL. The curve identified *Xkalman0.DVL_actif* indicates whereas the DVL is active(up level) or not(down level). In Fig. 5, as anticipated, the DVL system as failed many times. For a short time failure, the use of the preceding velocity allows the filter to keep its curve on the bathymeter curve. However, if the DVL is down for a longer period, the filter does not give acceptable results. There is an example of that situation starting at 22 s in fig. 5.

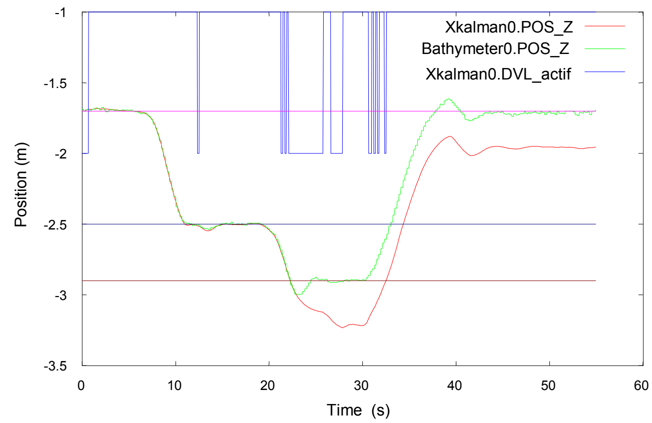

Fig.5 Experimental results of the impact of DVL failures on the position estimate.

For the Z coordinate, since the bathymeter has a fairly good accuracy and has a relatively high bandwidth, the algorithm uses its signal during a DVL failure instead of performing the time update using the preceding valid velocity.

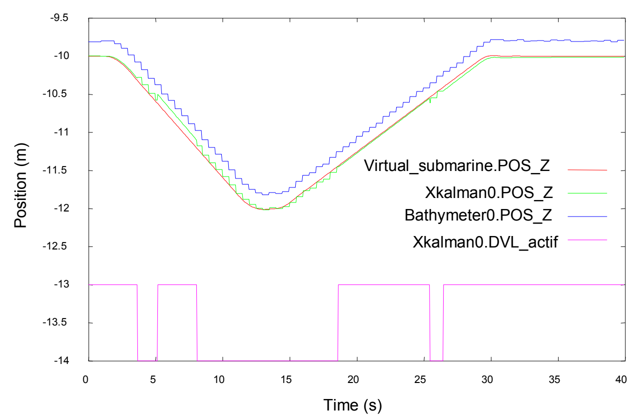

Fig.6 Experimental results of the Z position estimate during DVL failures.

VII. Conclusion

A navigation system that uses Kalman filtering to merge data received from an acoustic position system, a bathymeter and a DVL has been developed and implemented in simulation and in the real submarine. The impact of the delay from the acoustic data and the failure of the DVL on the position estimate have been highlighted by simulation results. The algorithm of the Kalman filter includes a correction for a fixed time delay of the acoustic system and the simulation results shows an appreciable improvement of the position estimate. However it is known that the time delay is not fixed. A model of this time delay should be developed in order to get the complete benefits of this development. During short DVL failures, the navigation algorithm compensate for the missing information. Both simulations and experiments show that a better position estimate is obtained. Finally it is of prime importance to measure accurately the position and orientation of the position systems on the vehicle in order to perform the coordinate transformations relative to the local frame precisely.

References

[1] Côté, J., Lavallée, J. "Augmented Reality Graphic Interface for Upstream Dam Inspection", *SPIE* - Telemanipulator and Telepresence Technologies II, Philadelphia, October 1995.

[2] Mehra, R., Seereeram, S., Bayard, D., Hadaegh, F. "Adaptive Kalman Filtering, Failure Detection and Identification for Spacecraft Attitude Estimation", *4th IEEE Conference on Control Applications*, 1995, 176-181.

[3] Magill, D.T. "Optimal Adaptive Estimation of Sampled Stochastic Processes", *IEEE Transactions on Automatic Control*, AC-10(4) : 434-439, October 1965.

[4] Brown, R.G., Hwang, P.Y.C. *Introduction to Random Signals and Applied Kalman Filtering*, 3rd edition, John Wiley & Sons, 1997.

[5] Whitcomb, L. L., Yoerger, D. R., Hanumant, S. "Combined Doppler/LBL Based Navigation of Underwater Vehicles," Proc. of the 11th International Symposium on Unmanned Untethered Submersible Technology, Durham, NH, August 1999.

[6] Spindel, R. C., Porer, R.P., Marquet, W. M., Durham, J. L. "A high-resolution pulse-Doppler underwater acoustic navigation system." IEEE Journal of Oceanic Engineering, vol.OE-1, no.1, pp. 6-13, 1976.