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Recent advances in navigation of underwater remotely operated vehicles

Avances recientes en la navegación de vehículos submarinos operados remotamente

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Abstract

A review of the most significant technical papers related to the navigation of underwater remotely operated vehicles is presented, with special interest in aided inertial navigation. Sensors used for implementation, fusion algorithms and models that describe the navigation systems are presented. From this review, it was concluded that the implementation of an estimator, based on the vehicle kinematic and dynamic models, limits the growth of the estimated error, even in case that the only available information is that provided by an inertial measurement unit.

Keywords: Aided inertial navigation, underwater navigation, underwater remotely operated vehicles

Resumen

Se presenta una revisión de las publicaciones técnicas más significativas sobre la navegación de vehículos submarinos operados remotamente, con especial interés en la navegación inercial asistida. Se definen los sensores que se utilizan para su implementación, los algoritmos de estimación y los modelos que describen los sistemas de navegación. Con esta revisión, se concluye que la implementación de un estimador basado en los modelos cinemático y dinámico del vehículo ayuda a limitar el crecimiento del error de estimación, incluso cuando sólo está disponible la información proporcionada por una unidad de medición inercial.

Palabras clave: Navegación submarina, navegación inercial asistida, vehículos operados remotamente

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Introduction

In the last ten years, maritime research has been addressed towards the development of Autonomous Underwater Vehicles (AUV), in order to explore areas where Underwater Remotely Operated Vehicles (UROV) can not be used; for example, to navigate under ice or to perform missions where accompaniment from a support vessel is prohibited [1].

However, UROVs are still designed for intervention or exploration tasks in delimited areas where one or more manipulators are required for maneuvering in real time, and consequently energy consumption could be high. Thus, an umbilical cable becomes important to provide energy and ensure the recovery of the robot [2].

Also, there is an interest in mini/micro ROVs because their agility, ease of transport, deployment and recover, and their relatively low cost. These vehicles and AUVs are being more used for monitoring and exploration [3].

The main challenge into the development of underwater vehicles is to obtain accurate positioning systems since aquatic environment is a scenario where it is not possible to have absolute global positioning signals, as those obtained with GPS. Therefore, the challenges related to localization of underwater robots still apply.

Whether in the ROVs or AUVs area, to improve precision of vehicle's states estimation, in spite of absence of sensors or technology, is a major goal.

Most of state of the art reviews about underwater navigation are addresed to AUVs. For example, [4] proposes the classification of the navigation techniques used as: inertial navigation, acoustic navigation, and geophysical navigation. [5] takes up this classification and makes a comparison of the three classes, defining what technique can be used depending on the needs of the AUV's missions. [6] and [7] not only present the drawbacks in the localization of AUVs and the most used solutions, but also address other design aspects such as mechanical structure, communications, and software and hardware architecture. Likewise, [8] reviews the sensors used in underwater navigation and proposes some challenges around the same topic.

This paper is an updated review of the most significant technical papers dealing with the navigation systems designed for UROVs, with a main interest in the aided inertial navigation and the algorithms to estimate position, orientation, linear velocities and angular rates of the robot.

The paper is organized as follows. In section II, the navigation problem is exposed from the approach of underwater vehicles modeling. Section III summarizes the existing navigation techniques following the well established classification, pointing out the publications where these methods have contributed to the UROVs' localization. Section IV presents the aided inertial navigation, describing the UROVs' navigation systems, the fusion algorithms, and the new research tendencies. Finally, section V closes the paper with the conclusions obtained by the review.

Underwater vehicles modeling

Float structures, vessels and partially or completely submerged vehicles such as UROVs are part of the marine craft category [9]. Their kinematics is described using two reference frames: inertial frame and body-fixed frame.

Inertial reference frame has its origin in an arbitrary point on the surface of the Earth and it consists of three perpendicular axes following the right hand rule: x indicates North, y points to the East, and z points towards the Earth center [10]. This frame is considered inertial because rotation of the Earth does not affect significantly the marine vehicles at low speed [11].

Likewise, the body-fixed frame consists of three axes according to the right hand rule: x goes from stern to bow, y from port to starboard, and z indicates the UROV's descent direction or the increasing in depth from the sea surface. Commonly, vehicle reference axes match with its inertia axes and the center of gravity is the origin of this reference frame [10].

The position vector of (1) is obtained by using the three vehicle linear displacements referenced on the inertial frame. In the same way, rotations around each axis of the Earth system, represented by the Euler angles, are used to obtain the orientation vector of (2). Vehicle linear and angular velocities expressed in the body-fixed frame through the vectors of (3) and (4) are obtained by using position and orientation rates, respectively.

$$\eta_1 = \begin{bmatrix} x & y & z \end{bmatrix}^T \tag{1}$$

$$\eta_2 = \begin{bmatrix} \phi & \theta & \psi \end{bmatrix}^T \tag{2}$$

$$\nu_1 = \begin{bmatrix} u & v & w \end{bmatrix}^T \tag{3}$$

$$\nu_2 = \begin{bmatrix} p & q & r \end{bmatrix}^T \tag{4}$$

According to the above expressions, six degrees of freedom in each frame are identified and they correspond to the six independent coordinates required to define the twelve states of the vehicle: into the inertial positions and orientations, linear velocities and angular rates.

Figure 1 shows the relation between the UROV's reference frames and its states. By following the Society of Naval architects and Marine Engineers (SNAME) [12], linear motion directions are named surge, sway, and heave, and the rotational ones roll, pitch, and yaw.

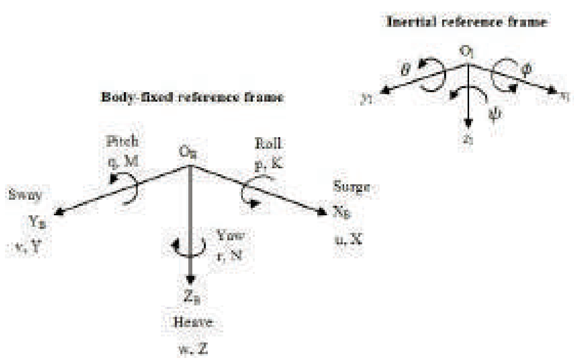

Figure 1 Reference frames of an UROV

One of the main problems to operate underwater robotics is related to the localization task, due to the absence of a single sensor able to provide information about all the vehicle's states. Moreover, the GPS cannot be used under water because its signals are strongly attenuated [13]. An alternative solution for this problem is a set of sensors installed in the vehicle to measure directly positions and orientations, or linear velocities and angular rates. With these measurements, it is possible to do a framework transformation and to determine the inertial variables from (5) to (8) [14].

Matrices of equations (7) and (8) represent the three consecutive rotations needed to transform a vector from the body-fixed reference frame: into inertial reference frame. Matrix transforms linear velocities in inertial velocities, and transforms angular rates into the corresponding angular displacement derivatives. The order of rotations is not arbitrary; vector is rotated by around axis of inertial frame, then by around the axis resulting from rotation around , and finally by around axis resulting from the two previous rotations [15].

$$\dot{\eta}_1 \quad J_1 \nu_1 \tag{5}$$

$$\dot{\eta}_2 = \boldsymbol{J}_2 \nu_2 \tag{6}$$

$$J_1(\eta_2) \begin{bmatrix} c\theta c\psi & (\quad c\phi s\psi + s\phi s\theta c\psi) & (s\phi s\psi + c\phi s\theta c\psi) \\ c\theta s\psi & (c\phi c\psi + s\phi s\theta s\psi) & (\quad s\phi c\psi + c\phi s\theta s\psi) \\ s\theta & c\theta s\psi & c\theta c\phi \end{bmatrix} \tag{7}$$

$$\boldsymbol{J}_2(\boldsymbol{\eta}_2) = \left(\frac{1}{c\theta}\right) \begin{bmatrix} c\theta & s\phi s\theta & c\phi s\theta \\ 0 & c\phi c\theta & -s\phi c\theta \\ 0 & s\phi & c\phi \end{bmatrix} \tag{8}$$

Existing navigation techniques

The process of determining the UROV's states, related to a reference frame, is known as navigation [2, 16]. Nowadays, there are different sensors used to detect motion and their selection depends on the navigation technique adopted. These techniques are presented next, emphasising on the aided inertial navigation.

Dead reckoning and inertial navigation

Dead reckoning is the most common and established navigation method [4, 17]. It uses measurements of the vehicle linear velocity and deviation from the magnetic North to calculate how much the vehicle has moved from a starting point [4]. The new vehicle position is determined by integrating the measured velocity, and the orientation corresponds to the deviation from magnetic North.

The most used sensors in dead reckoning are the compass and the speed sensor based on Doppler Effect or Doppler Velocity Log (DVL) [4, 17]. The former orientates itself according to the Earth magnetic field. This sensor is widely used in underwater vehicles due to its low cost. However, magnetic disturbances caused by the structure of the robot and its systems can generate significant errors [8].

On the other hand, sensors based on Doppler Effect measure velocity relative to the water or to the sea floor. In the first case, its main disadvantage is its inability to register the velocity components introduced by the ocean currents, generating incorrect estimation of positions [4]. The second one uses several transducers oriented on different angles that continuously send an acoustic signal of certain frequency towards the sea floor. As the underwater vehicle is moving, the signal reflected by the seabed changes in its frequency due to Doppler effect and the difference between the sent and received signals is used to estimate the vehicle's velocity [6].

As an alternative, the Correlation Velocity Log (CVL) is used. It is based on the same principle that DVL, but it emits two consecutive pings. The obtained echoes are compared and used to calculate velocity [6].

To utilize the DVL and CVL, the vehicle has to move slowly so that both sensors can record the reflected signal, and its distance from the sea floor should be a maximum of 300 meters [5, 7].

In inertial navigation, the variables measured are the linear acceleration and the angular rate experimented by the vehicle, which corresponds to a direct measurement of and in (3) and (4) respectively. One integration in time of the angular rate allows the UROV to calculate its orientation; also the double integration in time of the acceleration will determine the position. To perform the above procedure, three orthogonal accelerometers and gyroscopes can be used, or a sensor of each kind need to be arranged to register the motion change in the three body-fixed axis.

When the sensors are contained in a single device, it is named Inertial Measurement Unit (IMU). If a processing unit is included to correct the measurements and compensate for temperature effects, vibrations, etc., the whole set is named Inertial Navigation System (INS). Commonly, the INS receives its name according to the technology employed for the gyroscopes fabrication. The most used are the fibre optic and ring laser [18].

Dead reckoning and inertial navigation are used in low cost UROVs. For example, [19] used a 6 DOF IMU with three MEMS accelerometers and gyroscopes to implement an INS inside the PHANTOM S2 UROV. The test performed with the system at rest allowed to determine the statistics of the signals provided by each sensor, that is, the mean and the standard deviation. In addition, this work presents results about misalignment errors and a test where it was found that the errors generated by gyroscopes, belonging to that IMU in particular, cannot be considered as white noise.

[20] also designed and implemented a low cost INS for a particular UROV. He designed an IMU composed by a three axis accelerometer, a two axis gyroscope to sense the roll and pitch motion, and a single axe gyroscope to sense yaw. The information measured by the IMU is transmitted to an embedded computer in the UROV, where it is transformed in the inertial frame and the integration process is performed to calculate the position and orientation vectors.

In the report, some drawbacks related to the sensor configuration are mentioned, and the implementation of a Kalman filter in Matlab to reduce the navigation errors is suggested.

[21] proposes the inclusion of a DVL in the navigation system of VideoRay Pro4 mini-ROV. The Doppler effect sensor is small enough to be attached to the UROV, and it has a compass and other devices to detect roll, pitch, and yaw motion.

Although the inertial navigation is able to determine the vehicle's states [22], the small errors in acceleration and angular rate are integrated as the vehicle moves, causing bigger errors in the linear velocity, position and orientation calculated [18]. The drift increase rate, dependent on ocean currents, robot's velocity and measurement devices quality, can achieve a threshold where navigation becomes unacceptable [4, 17].

The first strategy to reduce the errors of this technique consists in determining the sources of error belonging to the sensors, as is proposed by [23] and [24]. Each author performed tests with an IMU at rest to define its parameters. They coincide in that a bad calibration of gyroscope makes a negative contribution to navigation results because the integration of gyroscope measurements is used to determine the device orientation, in (2), and later, the transformation matrices and in (7) and (8) respectively.

Likewise, the drift can be limited resetting the vehicle's position and orientation with respect to an inertial reference such as GPS. For UROVs, this is possible sending the complementary information through the umbilical cable [7], but in AUVs the procedure becomes unachivable when the vehicle is in deep water [5].

Acoustic navigation

Unlike the electromagnetic signals that suffer a high attenuation, the acoustic energy can be propagated adequately to significant distances in aquatic medium and therefore, it results in a viable alternative for positioning of unmanned underwater vehicles [4, 25].

This technique uses a set of acoustic devices and a ping is transmitted among them [5]. The time between the sending and return of the signal is used to calculate the distance that the vehicle has moved [8]. Depending on the number and the deployment of the acoustic elements as well as the signals frequency, this kind of navigation is classified as: Long BaseLine (LBL), Short BaseLine (SBL), and Ultra Short BaseLine (USBL) [25, 26]. All of these require a precise knowledge of the water speed profile which can be difficult to obtain in areas where it changes because of the temperature and density conditions [8].

LBL

These systems utilize at least three transponders mounted on the operation area, and one transponder mounted on the underwater vehicle [25]. The transmitters-responders can be deployed in seabed or in the surface [17], forming a geometric arrangement [18]. The maximum distance between the vehicle and acoustic transponders can be up to six kilometers [25].

To determine the position, the vehicle sends an acoustic signal to each transponder and they respond to the call. Thereafter, a triangulation is made using the signal time of flight [5].

To save the vehicle's energy, the transponder on the robot can be replaced by a receptor of the signals emitted by the rest of devices, each one to a different frequency and in an established sequence. According to the order in wich the waves arrive, the vehicle reconstructs its position [4].

Among the three types of acoustic navigation, the LBL systems provide the higher precision. However, the deployment and calibration of transponders require a considerable time and expert operators [26].

SBL

In this case, the transponders are not mounted on seabed or on the surface, but on the hull of an assistance vessel. The vehicle determines its position, related to this ship, when it calculates the arriving time of each of the acoustic signals returned by the set of transponders. Depending on the vessel shape, the acoustic devices are implemented in a distance of 10 to 50 meters among them [25].

This system has the advantage of providing a good level of accuracy. Its complexity is lower than LBL arrangements because the acoustic devices are installed directly on the assistance ship, but a rigorous calibration and the implementation of additional sensors to obtain an absolute position is needed [26].

[27] presents the integration of SHARPS system into the JASON/MEDEA array. The net of receivers is installed in the UROV JASON while the transmitter is mounted on MEDEA. When an acoustic signal is sent, the receivers provide information about the time of flight and the system determines MEDEA's position related to UROV JASON. As strategy to calculate the accuracy of the estimate, the Cramér Rao Lower Bound technique (CRLB) is used. Within the advantages, the authors highlight the insensitivity of the system to the UROV's hydraulic noise, which allows obtaining a high precision localization.

USBL

The operating principle of this technique is similar to SBL systems, but the distance among the transponders mounted on the vessel is about 10 centimeters [25]. The system measures the phase shift of the acoustic signal arriving to the array devices to calculate the orientation of the vehicle related to them. If these signals are returned to the robot, it can calculate its position according to the time of flight [4]. Among the three kinds of acoustic navigation, this technique is the most sensitive to the noise and to the calibration errors.

[28] makes a review of some USBL systems commercially available and propose the implementation of the inverted USBL. The application allows monitoring the position of an UROV through a node installed in the seabed, and a control station on the surface. The latter sends an acoustic signal to the node for its transmission to the UROV. The ping is returned to the node and processed to calculate the vehicle's position and orientation using a different approach to conventional methods for acoustic navigation.

Geophysical navigation or terrain navigation

This technique allows estimating the position in the inertial reference frame. A set of sensors extract certain geophysical characteristics of the operation area, as those related with bathymetry, the magnetic field, or gravitational anomalies. These parameters are compared with an a priori map of the region, which contains the distribution of those properties, or are employed to build a new map to estimate the vehicle position [4]. The success of the procedure in any of the two cases depends on the presence of the adequate characteristics and the sensors ability to extract them [5].

The most common measurement devices are the sonar and the cameras [5]. The former works sending an ultrasonic sound that is redirected by the obstacles or the seabed. The signals detected by a hydrophones array are reconstructed digitally to generate a map of the explored region [20, 29]. On the other hand, cameras are good if the vehicle is close to the sea floor and *y* has φ adequate illumination [5].

The geophysical navigation provides the best accuracy compared to the other techniques, but it requires the implementation of equipment with high energy consumption, besides the computational cost associated to the processing of the obtained measurements [7].

[30] discusses about the usage of this technique in AUVs.They also unify the nomenclature of this topic through a comparative table including the measurement models, sensors, and the probabilistic approaches used in the estimates.

Aided inertial navigation

The most recent publications about the navigation of underwater remotely operated vehicles show a combination of the methods described in the above sections. Inertial navigation is common in all them.

According to the IEEE standard for inertial systems terminology [31], the aiding consists in including no inertial information like measurements provided by acoustic sensors or those used for geophysical recognition. However, the addition of other measurement devices is not the only way to aid the estimates. As alternative, restrictions in the movement can be established or a model that describes the kinematics and dynamics of the system can be used. Whatever the case, the implementation of an algorithm to fuse the modeling and measurements is required.

[32] and [33] make a classification of the techniques for the fusion of data from multiple sensors. Following these authors, the filtering and estimation algorithms combine the signals from similar sensors to obtain an estimate of the vehicle's states. The information from the measurement devices is modeled as random variables that have been corrupted with noise, which requires a precise knowledge of the covariances associated. Kalman filter versions are commonly used to integrate the INS measurements with acoustic sensors, for example LBL, because they provide optimum estimates in a statistical sense.

Figure 2 presents the Kalman filter cycle for discrete linear systems. Two stages are observed: prediction and update. During prediction, the transition matrix A, input matrix B, previous state x_{k-1}, previous error covariance P_{k-1}, input u_k, and process noise covariance matrix Q are used to propagate the state estimate $\boldsymbol{x}_k^-$ and the error covariance matrix $\boldsymbol{P}_k^-$ ahead in time. When a new measurement z_k is available, $\boldsymbol{x}_k^+$ and $\boldsymbol{P}_k^+$ are updated through the Kalman gain K_k that involves the observation matrix H and the measurement noise covariance matrix R [34].

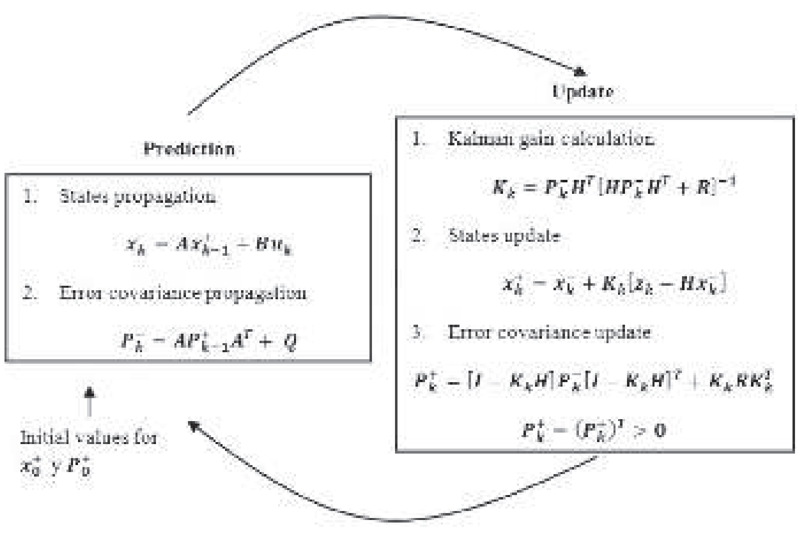

Figure 2 Kalman filter cycle for discrete linear systems. Adapted from [34]

Kalman filters can be implemented as indirect or direct feedback [35, 36]. In the first configuration, the position, velocity and orientation data obtained with an aiding system is subtracted from the information of these states provided by the INS to generate an observation error that constitutes the filter input. Further, the navigation errors are estimated and subtracted from the INS calculations. In direct feedback, the same procedure is made, but the estimated errors are used to limit the INS drift. The reader is referred to [35] and [36] for further details.

The barest error model to perform the prediction is (13). The variation rates of position errors are the velocity errors; variation rates in state δV are described as an acceleration error, and variation rates in orientations errors are modeled as errors in angular rates measurements. Matrix Q is given by (14), where δP is noise associated to velocity integration inside the INS to calculate position, and δA_B and $\delta\omega_B$ are the accelerometer and gyroscope noise components. This model is deduced assuming small errors in orientation angles [37]. [38] presents INS models where errors do not meet this restriction.

$$\begin{bmatrix} \delta\dot{P} \\ \delta\dot{V} \\ \delta\dot{\Psi} \end{bmatrix} = \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & A_J \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta P \\ \delta V \\ \delta \Psi \end{bmatrix} + \begin{bmatrix} 0 \\ J_1 \delta A_B \\ -J_1 \delta\omega_B \end{bmatrix} \qquad (13)$$

$$Q = \begin{bmatrix} \delta P & 0 & 0 \\ 0 & \delta A_B & 0 \\ 0 & 0 & \delta\omega_B \end{bmatrix} \qquad (14)$$

[39] makes a comparison of the Kalman filter performance in direct and indirect feedback, when it is applied to a navigation system compound of an INS and a DGPS during a 96 minutes simulation. Their results show a tendency to divergence in the direct feedback filter since the error grows with time. On the other hand, indirect feedback configuration offers better results because the estimated errors oscillate around zero during most of the simulation.

The growth of the estimated error in direct feedback configuration is due to the INS drift associated to position, velocity, and orientation, in conjunction with noise and other sensors inaccuracies. As time passes, the difference between states calculated by INS, and measurements from additional devices is bigger, violating the restriction adopted to maintain the linearity of model equations [36].

Recent researches combine direct and indirect feedback to improve the results offered by the filter. For example, [37] uses this strategy in an INS/DVL navigation system, where the estimated errors are subtracted from position, velocity and orientation from INS, and in turn are used to start a new iteration in the filter. Thus, the corrected vehicle's states are used to calculate the observation error and to limit the output growth. In the published results, a difference about one meter between the real trajectory and that followed by the submarine using aided inertial navigation is observed after two hours and five minutes of simulation. In a second test, the DVL measurements error was reduced and a difference between trajectories lower one meter was obtained.

The model in (13) is not the only option to implement the linear Kalman filter in navigation as is observed in the work published by [40]. In this research, the UROV's localization system is compound of an INS, a DVL, and an acoustic arrangement. The measurements of these last two systems are expressed in body-fixed frame, so the INS information is used to make the transformation to inertial frame. Thereafter, the states of position and orientation are estimated in the Kalman filter. A_k matrix is linear because it relates directly the rate of change of position and velocity with these states in the inertial frame. The input corresponds to the DVL measurements once they have been transformed, and position from acoustic arrangement constitutes the filter observation. According to this implementation, Q matrix includes the DVL noise and R the acoustic system noise. To test the estimator, [40] simulates the UROV's dynamics to obtain the filter observations.

If the Kalman filter seeks to directly estimate the vehicle's states, it is necessary to implement a direct configuration as that shown in Figure 3. Linear acceleration and angular rate measured by the IMU, plus additional measurements from aiding sensors, feed the filter for the estimation. Here, the model may vary according to design criteria and required accuracy.

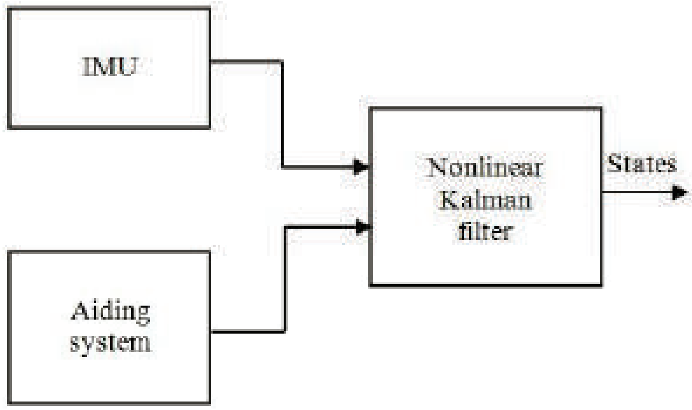

Figure 3 Direct Kalman filter

[41] integrates an IMU and a Laser Vision System (LVS) in the micro-ROV VideoRay Pro using a Wiener process as model in which the vehicle acceleration is part of the states and the input is modeled as white noise [42]. The IMU provides the linear acceleration components and the angular rate in *z* axis, while the LVS provides linear velocities and yaw orientation. The filter, when compared with LVS information, presents good results even in the situation where UROV loses the reference point of the vision system and the estimate is only updated with the IMU.

[11] also implements a Kalman filter to estimate the orientation of VideoRay Pro, but using a linear model that describes the information provided by three gyroscopes. The state vector is composed of roll, pitch and yaw motion, and their associated deviation. The system inputs are the angular rate and the measurements correspond to the three Euler angles calculated independently based on information provided by three accelerometers. All measurements are transformed from body-fixed frame to the inertial frame before starting the filter.

[11] analyzes the system behavior performing free inertial navigation and then applying the Kalman filter. In the first case, an unlimited growth in position, linear velocity, and orientation components is observed despite the UROV was at rest which corroborates the drift of this technique. In the second test, orientation estimated values oscillate around zero. Finally, when a motion in pitch is caused, also a variation occurs in roll due to the low coupling among the vehicle degrees of freedom.

Navigation in non controlled environments

Some works such as [11] and [13] were performed in a semi-controlled environment such as a swimming pool. However, when the UROV is maneuvered at sea, different forces and moments caused by the fluid affect the robot's motion and should be included in the fusion algorithm modeling to improve its performance.

[14] propposed the general model of motion of (15) associated with the UROV/AUV hydrodynamic forces exposed above.

$$\boldsymbol{M}\dot{\boldsymbol{v}} + \boldsymbol{C}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{D}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{g}(\boldsymbol{\eta}) = \boldsymbol{\tau}_{prop} + \boldsymbol{\tau}_{cab} + \boldsymbol{\tau}_{ext} \quad (15)$$
$$\dot{\boldsymbol{\eta}} = \boldsymbol{J}\boldsymbol{v}$$

where $\boldsymbol{M}$ is the total mass matrix; $\mathbf{C(v)}$ is the centripetal and Coriolis forces matrix; $\boldsymbol{D(v)}$ is the hydrodynamic damping matrix; $\boldsymbol{g(\eta)}$ is the restoring forces vector; $\boldsymbol{\tau}_{prop}$ is the resultant forces and moments vector: $[X\ Y\ Z\ K\ M\ N]$; $\boldsymbol{\tau}_{cab}$ is the cable disturbances vector, and, $\boldsymbol{\tau}_{ext}$ is the environmental disturbances vector.

Equation (15) brings together the UROV's dynamics, kinematics and mechanics in a nonlinear expression that depends on the states defined in (9) - (10) [43]. Since this model is nonlinear, equations of figure 2 must be modified to account for nonlinearities. Such modifications are known as the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). Both of them estimate the states of the system presented in (16).

$$\dot{\boldsymbol{x}} = \boldsymbol{f}\left(\boldsymbol{x},\boldsymbol{u}\right) + \boldsymbol{w} \qquad \boldsymbol{z} = \boldsymbol{h}\left(\boldsymbol{x}\right) + \boldsymbol{v} \qquad (16)$$

The EKF introduces the Jacobian operator, through a first order Taylor series expansion, to make a linear approximation of $\boldsymbol{f(x,u)}$ and $\boldsymbol{h(x)}$, and generate the matrices $\boldsymbol{F}$ and $\boldsymbol{H}$ of (18).

$$\boldsymbol{F} = \left.\frac{\partial f\left(x,u\right)}{\partial x}\right|_{x=\hat{x}_k^+} \quad \boldsymbol{H} = \left.\frac{\partial h\left(x\right)}{\partial x}\right|_{x=\hat{x}_{k+1}^-} \qquad (18)$$

To apply the Kalman cycle, (15) has to be transformed to the discrete domain, and (18) and (19) are replaced where necessary in the expressions of figure 2. On the other hand, the UKF does not use a linear approximation, but an "unscented" transformation which prevents the influence of nonlinearities on the estimation. For a more detailed explanation of this transformation, the reader is referred to [44].

[45] simulates the EKF to estimate the linear velocity and position of ROPOS UROV, along with ocean current components. The filter model coincides with (15) but the $\boldsymbol{g(\eta)}$ and $\boldsymbol{C(v)}$ effects are neglected due to the vehicle neutral buoyancy, and the approach of [46]. Observations include linear velocities measured by a gyro-compass and a DVL; the position coordinates registered by an USBL system, and the depth calculated using a pressure sensor. In this case, as the observations are direct measures of the states, $\boldsymbol{h(x)}$ is linear. The results show a good performance of the filter becoming more noticeable when the USBL and DVL information is not available.

The filter implemented in [45] was tested by simulating the sensor signals through (15) taking into account the simplifications mentioned. Tuning of $\boldsymbol{P}_o$, $\boldsymbol{Q}$, and $\boldsymbol{R}$ matrices is addressed in [47].

Likewise, [48] developed two observers to estimate the position and orientation with respect to the vertical (yaw), along with the associated velocities of UROV MINERVA. One of them uses (15) as model, neglecting the Coriolis and centripetal forces matrix, and the quadratic components of the hydrodynamic damping matrix. The Kalman filter equations of figure 2 are used, where linearity around ψ is achieved in the $\boldsymbol{A}_k$ matrix. The second algorithm is an EKF which includes the full model of UROV in the possible degrees of freedom. The filter input and measurement equation are the same as in the previous case. After a set of 300 seconds tests, the authors conclude that the EKF has better performance than the KF because it significantly reduces the estimation error. In these results, a convergence of the extended filter is observed even when some measurements are not available and the system works with dead reckoning.

The works previously presented reduce the number of differential equations assuming that some of the states can be obtained directly through the sensors installed in the vehicle [45], or the model is simplified according to the possible degrees of freedom [48].

However, the extended Kalman filter also yields good results when it estimates the UROV's twelve states as is presented by [49]. This work includes in the state vector three additional parameters representing the umbilical cable disturbances. The dynamic of (15) is used to model the position, orientation, and linear velocity rate of change, while the angular accelerations are assumed constant. The filter observations correspond to the direct measurements of the states provided by a pressure sensor, a compass, and an IMU, together with measurements from a DVL and a SBL that introduce nonlinearities in $h(x)$. In all analysed cases, it was found that the EKF provides more accurate information about the states that using only the measurements from sensors without fusing them.

In contrast, [50] shows that the results yielded by the EKF may not be favorable. The linear velocities estimated by the EKF in a linear path, using the complete model of the vehicle and measurements from an IMU and a DVL, are quite similar to the reference velocities provided only by the DVL. On the other hand, the estimated r when the UROV makes a turn is bad in comparison with the angular rate estimated by EKF using a nonlinear model of the inertial sensors, and the same observations. However, the poor performance of the filter in [50] can be attributed to inadequate identification of the UROV's model parameters as is stated by [51].

According to the majority of the works cited in this section, the extended Kalman filter represents a promising alternative for the fusion of measurements provided by sensors of different types, in order to contribute to the navigation of underwater vehicles, particularly UROV. However, other publications present the UKF as a valid option to perform the same task. For example, [52] updated the work of [41] implementing an UKF to improve the estimate of the VideoRay Pro III states.

Conclusions

The main techniques for underwater navigation were presented. Aided inertial navigation is emphasised as a good strategy for localization of remotely operated vehicles because, despite the boom achieved by AUVs, UROVs are still a good option to develop missions which require a real time update of the information recorded in the area of operation, and the tools used involve significant energy consumption. Within each category exposed, some of the works that provide information about the techniques behavior, measuring devices, and processing needed to calculate or estimate parameters were cited.

Free inertial navigation is independent on external signals and employs low cost sensors, but generates an error accumulation due to the drift integration over the time. Acoustic navigation offers a higher precision that inertial technique, it uses the sound that propagates better in water, but it raises the mission cost because a deployment and a subsequent recovery of the transponders are required. Geophysical navigation is the more accurate individual strategy, but it requires an a priori map of the operation area or the implementation of dedicate sensors to register certain characteristics and build an online map. This also increases the mission cost.

According to reviewed publications, the researchers have focused their efforts on the combination of existing underwater navigation methods to try to limit their errors and take advantage of their strengths. This has resulted in aided inertial navigation, which uses Kalman Filtering as a robust strategy of integration, taking into account the process and observations noise.

Recent advances show an interest to research into fusion algorithms when sensor dropout occurs. This has conducted to a deepest analysis of the models that describes the systems and which are used to propagate the states. Extended Kalman filter is the most widely used fusion algorithm since it can be used when the sensors does not measure position, orientation and velocity directly, and the filter inputs are related with the states change rate through a non linear expression.

The complete model of an UROV that involves its kinematics, dynamics and mechanics, performs an adequate propagation of states and contributes significantly to limit the error when there is a fault in the sensors and the only available information is that from inertial measurements.

The implementation of linear Kalman filter facilitates the definition of the error covariance matrix and process and measurement noise matrices because these parameters are given by the noise characteristics of the sensors used. In the nonlinear versions of the filter, the definition of these matrices requires a more dedicated tuning process that involves trial and error testing.

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