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A novel intelligent adaptive Kalman Filter for estimating the Submarine's velocity: With experimental evaluation

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ABSTRACT

In this paper, an intelligent adaptive algorithm based on the integrated Inertial Navigation System (INS) is presented for estimating the velocity of an Autonomous Underwater Vehicle (AUV). The most common algorithm for incorporating the navigation data is Kalman Filter (KF). In the conventional KF algorithm, the covariance matrix of measurement noise is considered as a constant through running time. The noise covariance in the Adaptive Kalman Filter (AKF), is estimated through processing the innovation sequence inside a window of constant length. In actual conditions, the correct window length to achieve the best estimation, depends on the operational conditions. In this paper, proper window length in the adaptive algorithm is estimated by processing the probability density function of the innovation sequence at each time step; so the window length in the proposed algorithm is variable due to condition changes. The proposed integrated navigation system consists of a three-axis Inertial Measurement Unit (IMU) and a three-axis Doppler Velocity Log (DVL). The performance of the proposed system is evaluated through four sea tests using an AUV. Experimental results show that the proposed system has superior performance than the conventional KF algorithm and is similar to the optimum AKF(AKF with the best window length).

1. Introduction

Various sensors and methods are used to achieve the speed of underwater vehicles. Using ElectroMagnetic speed Log (EML), model-based methods and Doppler Velocity Log (DVL) is common to measure and calculate the speed of underwater vehicles. In the EML, when sea water passes through an electromagnetic field, a voltage is created and varies depending upon the speed of the water flow. The EML measures the voltage and translates it into the vessel's speed through water. There is a correlation between propeller rotation speed, propeller torque and relative advance speed in water. Hence the propeller rotation speed can be used to roughly estimate vehicle relative advance speed Allotta et al. (2015a, 2016b, 2015b). The EML and propeller model-based methods provide the speed relative to water not ground. While DVL calculates vehicle's velocity with respect to the sea bottom through emitting acoustic pulses toward seabed and measuring Doppler shift of returned pulses with respect to the emitted ones Gordon (1996). The DVL translates it into the vessel's speed over ground. Because of water speed, using the relative speed in navigation causes a slight error and it is better to use speed over ground to achieve an accurate navigation. Accordingly DVL is a widely used sensor for measuring the velocity of underwater vehicles Larsen (2000); Grenon et al. (2001); Lee et al. (2007); Tang et al. (2013); Gao et al. (2014); Allotta et al. (2016a); Emami and Taban (2017); Xu et al. (2017). This sensor calculates vessel's speed over ground through emitting acoustic pulses toward seabed. For this reason, the accuracy of the measured velocity depends on environmental conditions such as depth, kind of seabed and ambient acoustic noise Sonnenberg (1988); Farrell (2008). DVL's measurements are noisy and often contain outlier data; hence, using DVL individually may not be an appropriate way for accurate navigation. A prevalent approach for estimating underwater vehicle's velocity is to integrate DVL's measurements with accelerometer's signals. This method is used in the integrated Inertial Navigation System (INS) Lee and Jun (2007); Miller et al. (2010); Hegrenaes and Hallingstad (2011); Li et al. (2013, 2015); Shabani et al. (2015); Shabani and Gholami (2016); Chang et al. (2017).

Kalman Filter (KF) Kalman (1960) is the most conventional algorithm for data integration in navigation applications Brown and Hwang (2012); Grewal et al. (2013); Grewal and Andrews (2015). In the KF algorithm, the statistics of the filter, expressed by the process and measurement

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noise matrices are considered constant Mohamed (1999). These matrices are usually determined either through information presented by manufacturer or data analysis in stationary conditions Farrell (2008); Groves (2013). In actual conditions, noise covariance matrix varies during navigation time. Variations in the noise covariance matrix of DVL's measurements may be significant due to dependence of DVL on environmental conditions. This may cause destructive effects on estimation accuracy. Therefore, estimation algorithm with constant noise covariance must be replaced with an adaptive estimation algorithm throughout the estimation process.

Adaptive Kalman Filter (AKF) was first proposed by Mehra in 1970 where covariance matrices of process and measurement noises are estimated based on the variations of innovation sequence Mehra (1970, 1972). In navigation applications, this algorithm was first used by Mohamed and Schwarz for estimating the noise covariance matrix in the integrated Inertial Navigation System/Global Positioning System (INS/GPS) Mohamed and Schwarz (1999). The AKF has been widely used in air and land vehicles ever since Hide et al. (2003); Hu et al. (2003); Ding et al. (2007); Jwo and Weng (2008); Jiancheng and Sheng (2011). Regarding marine applications, some studies have been conducted in the recent years. For example, Gao and Li have proposed a Sage-Husa-based AKF for INS/DVL navigation system Gao and Li (2013). Gao et al. have suggested an adaptive noise estimator for integrated INS/DVL system Gao et al. (2015). Recently, Davari et al. have developed a multi-rate AKF for marine integrated navigation system Davari et al. (2016).

In the conventional AKF, a fixed-length window of innovation sequence is processed at every time instant and noise covariance is estimated inside this window Gao et al. (2015). The accuracy of innovation covariance matrix estimation depends on the window length. System dynamic specifications, vehicle manoeuvres and environmental factors may have a major impact on proper choice of this parameter Mohamed and Schwarz (1999). For example, in INS/DVL navigation, under the conditions that vehicle motion has high-frequency variations or outlier data in DVL's measurements occurs, the window length must adopt a small value to be able to detect rapid changes. Nonetheless, under the conditions that system dynamic changes mildly and the noise of DVL's measurement has steady distribution, it is better to select a large value for window length to achieve a better estimate of innovation covariance matrix. Since operational conditions of the system are not predictable, the variations of the DVL noise cannot be predicted; therefore it is not possible to determine an optimal window length.

In this paper, a novel intelligent integrated navigation system is presented, in which the length of estimation window is adaptively tuned through detecting the noise distribution changes along the innovation vector. Time instants of the variations occurred in the measurement noise are detected in order to determine a proper value for window length. Window length is set to a small value at these time instants. Also the window length is set to a large value at time instants at which the variance of DVL noise is constant. Maximum value is selected such that the location of considerable variations in the noise does not lie inside the window. Results of the experimental tests performed at sea show that the proposed algorithm is a proper solution to remove the confusion of designer in determining the window length.

Evaluation of the proposed algorithm has been done through an integrated navigation system composed of a three-axis Inertial Measurement Unit (IMU) and a three-axis DVL installed on an Autonomous Underwater Vehicle (AUV). In this paper, since the used AUV has mild dynamic, the covariance matrix of process noise is assumed to be constant.

The structure of the paper is as follows. After introduction, the equations related to the integrated navigation system are given in Section 2. In Section 3, the equations of the proposed algorithm are derived. In Section 4, experimental results of the proposed system will be presented. Finally, Section 5 draws a conclusion of the paper.

2. Integrated navigation system

In this section, first, system and measurement equations for INS/DVL integrated navigation system are expressed. Then, based on these equations, data integration equations are given.

2.1. System equations

In the proposed system, in order to estimate the horizontal velocity of an AUV, we integrate the INS with the DVL. In this system, the state vector consists of position, velocity and orientation of the AUV. Generally, kinematic equations of the INS is non-linear, and the general form of a continuous-time nonlinear state space model is as follows Simon (2006):

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{w}), \tag{1}$$

where $\mathbf{f(.)}$ is a nonlinear vector function, $\mathbf{x} = [(\mathbf{p}^n)^T, (\mathbf{v}^n)^T, \boldsymbol{\xi}^T]^T$ is the system state vector including position, velocity and attitude; $\mathbf{p}^n = [L, l, d]^T$ is the position vector and consists of latitude L, longitude l and depth d; $\mathbf{v}^n = [v_N, v_E, v_d]^T$ is the velocity vector in the navigation frame in which v_N, v_E and v_d are velocity components in the directions of true north, east and the local vertical, respectively. $\boldsymbol{\xi} = [\phi, \theta, \psi]^T$ is the orientation vector, and consists of roll ϕ, pitch θ and heading angle of the AUV ψ; $\mathbf{u} = [(\mathbf{f}^b)^T, (\boldsymbol{\omega}_{ib}^b)^T]^T$ is the control input vector where $\mathbf{f}^b = [f_x, f_y, f_z]^T$ is the vehicle's acceleration vector in the body frame, and $\boldsymbol{\omega}_{ib}^b = [p, q, r]^T$ is the body angular rate with respect to inertial frame resolved in the body frame. $\mathbf{w}$ is the process noise caused by uncertainty in $\mathbf{u}$, assumed as Gaussian noise with zero mean and Power Spectral Density (PSD) matrix $\mathbf{Q_c}$, and is expressed as follows:

$$\mathbf{w} = \left[\mathbf{w}_a^T, \mathbf{w}_g^T\right]^T, \tag{2}$$

where $\mathbf{w}_a = [w_{ax}, w_{ay}, w_{az}]^T$ and $\mathbf{w}_g = [w_{gx}, w_{gy}, w_{gz}]^T$ are the noise components of the accelerometer and gyroscope measurements. Because of independency between $\mathbf{w}_a$ and $\mathbf{w}_g$, $\mathbf{Q}_c$ can be formed as a diagonal matrix:

$$\mathbf{Q}_c = \begin{bmatrix} \sigma_a^2 \mathbf{I}_3 & 0_3 \\ 0_3 & \sigma_g^2 \mathbf{I}_3 \end{bmatrix}. \tag{3}$$

σ_a^2 and σ_g^2 are noise variances of the accelerometer and the gyroscope, respectively and $\mathbf{I}_3$ and 0_3 are 3×3 identity and zero matrices, respectively. System kinematic equation is a non-linear function and is expressed as follows Titterton and Weston (2004):

$$\mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{w}) = \begin{bmatrix} \boldsymbol{\Gamma} \mathbf{v}^n \\ \mathbf{C}_b^n(\mathbf{f}^b + \mathbf{w}_a) - \left(2\boldsymbol{\omega}_{ie}^n + \boldsymbol{\omega}_{en}^n\right) \times \mathbf{v}^n + \mathbf{g}^n \\ \boldsymbol{\Lambda}^{-1} \boldsymbol{\omega}_{nb}^b \end{bmatrix}, \tag{4}$$

where $\times$ denotes the cross product between two vectors and

$$\boldsymbol{\Gamma} = \begin{bmatrix} \dfrac{1}{R_N + d} & 0 & 0 \\ 0 & \dfrac{\sec L}{R_E + d} & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{5}$$

$$\boldsymbol{\omega}_{ie}^n = [\Omega \cos L \quad 0 \quad -\Omega \sin L]^T, \tag{6}$$

$$\boldsymbol{\omega}_{en}^n = \left[\frac{v_E}{R_E + d} \quad -\tfrac{v_N}{R_N + d} \quad -\tfrac{v_E}{R_E + d}\tan L\right]^T, \tag{7}$$