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An innovation based random weighting estimation mechanism for denoising fiber optic gyro drift signal

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ABSTRACT

In Interferometric Fiber Optic Gyroscope (IFOG), the diminution of random noise and drift error is a critical task. These errors degrade the performance of IFOG. In this paper, a modified adaptive Kalman gain correction (AKFG) algorithm is proposed to denoise IFOG signal. The covariance matrix of innovation sequence is estimated using weighted average window method in which the weights are randomly generated in the range [0, 1]. Innovation based random weighted estimation (IRWE)-AKFG is applied to denoise the IFOG drift signal. The Kalman gain is adaptively updated using the covariance matrix of innovation sequence. The proposed algorithm is applied for denoising IFOG signal under static and dynamic environment. Allan variance method is used to analyze and quantify the stochastic errors in IFOG sensor. The performance of the proposed algorithm is compared with Conventional Kalman filter (CKF) and the simulation results reveal that the proposed algorithm is an efficient algorithm for denoising the IFOG signal.

1. Introduction

In the Strapdown Inertial Navigation System (SINS), Interferometric Fiber Optic Gyroscope (IFOG) has been used for measuring the rotation angle. Recently, IFOG is being widely used for military and defense applications, due to its significant advantages such as small size, low cost, light weight, no moving parts, large dynamic range, low power consumption, and possible batch fabrication [1,2]. The performance of IFOG degrades due to the variation in environmental factors such as temperature, vibration, and pressure [3,4]. Among different types of error in the IFOG signal, random drift error leads to decrease the IFOG performance over a period of time. The precision of IFOG sensor depends on the bias drift and noise in the measurement [5]. IFOG sensor has mainly two types of error (i) deterministic error and (ii) stochastic error. Deterministic errors are due to the scale factor, bias and misalignment which can be eliminated by suitable calibration techniques in the laboratory environment. However, stochastic errors are due to the environmental temperature changes, electronic components and, other electronic equipment interfaced with it [6]. It is difficult to eliminate these errors by calibration. Thus stochastic models are required to characterize these errors and signal processing techniques are required to suppress these errors.

In signal processing, the frequency domain and time domain analysis have been used to analyze and quantify the stochastic errors of IFOG sensor. Allan variance has been used to quantify the stochastic errors like quantization noise (Q), angle random walk (N), bias instability (Bs), rate random walk (K) and rate ramp (R) are quantified [7,8]. In IFOG sensor, compensation methods have been used to eliminate the random noises and bias drift, to improve the accuracy of measurement [9,10]. Stochastic noise models like auto regressive (AR), moving average (MA), and auto regressive moving average (ARMA) have been used to determine the stochastic behavior of the gyro sensors [11–14]. Kalman filter is a recursive filter and widely used in the field of navigation system [15]. Conventional Kalman filter requires a prior knowledge of dynamic process and measurement models, in addition to the process and measurement noise of the system (IFOG). In real time application, theoretical behavior of the filter do not agree with its actual behaviour and leads to divergent problems [16]. Kalman filter requires accurate measurement error and process models to avoid the divergent effects.

To improve the practicability and to solve the divergent problems of Kalman filter, adaptive Kalman filter (AKF) have been developed [17]. AKF is classified into three types (a) innovation based adaptive estimation (IAE), (b) residual based adaptive estimation (RAE) and (c) multiple models based adaptive estimation (MMAE). In RAE and IAE Kalman filter, the innovation or residual vectors must be known a prior [18]. Covariance matching technique is a popular method being used to estimate the noise covariance matrix [19]. This technique uses slip window average method to

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estimate the noise covariance matrix [19]. Innovation or residual based adaptive estimation AKF has been explored in the design of INS [20,21]. In recent literature, AKF algorithms were used to compensate the gyro drift for improving the accuracy of gyro sensor [22–25]. In statistics and probability theory, random weighting estimation method is the emerging technique for evaluating the noise statistics [26]. It has many advantages like unbiased estimation, simple computation method and easy to solve large sample problems, further, need not to know the exact probability distribution of the characteristic parameters. To the best of authors knowledge, there has been very limited research regarding the use of random weighting method for adjusting the Kalman filter parameters and its application to gyro signal processing. The random weighting estimation is regarded to be a promising method for improving the accuracy of the gyroscopes [27–29]. In this paper, random weighting of innovation sequence with gain correction adaptive Kalman filter is developed for denoising the IFOG signal. The covariance matrix of innovation sequence is estimated by random weighting method.

The remainder of the paper is organized as follows; Section 2 explains the related theory of random weighting estimation method and its approach. Section 3 presents, CKF algorithm approach in adaptive Kalman filter method and an innovation based random weighting estimation approach and related method description. Section 4 describes the experimental and simulation results of proposed algorithms, followed by conclusions in Section 5.

2. Principle of Random weighting estimation

Suppose that $X_1, X_2, \ldots, X_n$ are the random variables, which are independent and identically distributed of observations. The common distribution function of random variables is $F(x)$, and the accompanying empirical distribution function is $F_n(x)$. Let $x_1, x_2, \ldots, x_n$ are the sample realization. In addition, we have denoted $X = (X_1, X_2, \ldots, X_n)$ and $x = (x_1, x_2, \ldots, x_n)$. Then, the corresponding empirical distribution function is expressed as [26–29]

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{(X_i<x)} \tag{1}$$

and the random weighting estimation of $F(x)$ can be represented as

$$H_n(x) = \sum_{i=1}^{n} V_i I_{(X_i<x)} \tag{2}$$

where $I_{(X_i<x)}$ is the indicator function, defined as

$$I_{X_i<x} = \begin{cases} 1, & I_{X_i<x}. \\ 0, & I_{X_i>x}. \end{cases}$$

and $[V_1, V_2, \ldots, V_n]$ is the random vector subject to Dirichlet distribution $D(1, 1, \ldots, 1)$, that is $\sum_{i=1}^{n} V_i = 1$ and the joint density function of $[V_1, V_2, \ldots, V_n]$ is $f(V_1, V_2, \ldots, V_n) = \tau_n$, where $(V_1, V_2, \ldots, V_n) \in D_n$ and $D_{n-1} = \{[V_1, V_2, \ldots, V_n : V_k > 0 (k = 1, 2, \ldots, n-1), \sum_{k=1}^{n-1} V_k < 1\}$.

3. Adaptive Kalman filtering

Kalman filter is a recursive estimator to estimate the state of a system and minimize the mean squared error of residuals. In recent years, Kalman filter was used for denoising the stochastic noises of inertial sensor to improve the precision of measurement [30].

3.1. Conventional Kalman filter

Conventional Kalman filter requires a prior knowledge of dynamic process and measurement models, in addition to the process and measurement noise of the IFOG [20]. Considering a linear dynamic system, measurement equations can be written as

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + w_{k-1} \tag{3}$$

$$\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \upsilon_k \tag{4}$$

where, $\mathbf{x}_k$ is the state vector at epoch k; $\mathbf{A}_k$ is the state transition matrix; w_{k-1} is the system noise; $\mathbf{z}_k$ is the observation at epoch k; $\mathbf{H}_k$ represents the observation matrix, υ_k is the measurement noise.

Let us assume that the process and measurement noises w_{k-1}, υ_k are white Gaussian with zero mean and independent from each other, following the below properties

$$E[w_{k-1}] = 0 \tag{5}$$

$$E[\upsilon_k] = 0 \tag{6}$$

$$E[w_k w_l^T] = \mathbf{Q}\delta_{kl} \tag{7}$$

$$E[\upsilon_k \upsilon_l^T] = \mathbf{R}\delta_{kl} \tag{8}$$

where δ_{kl} is Kronecker delta function, i.e.,

$$\delta_{kl} = \begin{cases} 1, & k = l. \\ 0, & \text{otherwise}. \end{cases}$$

The prediction equations can be expressed as

$$\hat{x}_k^- = \mathbf{A}_{k-1}\hat{x}_{k-1} \tag{9}$$

$$\hat{P}_k^- = \mathbf{A}_{k-1}\hat{P}_{k-1}\mathbf{A}_{k-1}^T + \mathbf{Q}_k \tag{10}$$

and the update equation can be expressed as

$$K_k = \hat{P}_k^-\mathbf{H}_k^T[\mathbf{H}_k\hat{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k]^{-1} \tag{11}$$

$$\hat{x}_k = \hat{x}_k^- + K_k[\mathbf{z}_k - \mathbf{H}_k\hat{x}_k^-] \tag{12}$$

$$\hat{P}_k = [I - K_k\mathbf{H}_k]\hat{P}_k^- \tag{13}$$

The initial state and error covariance matrix of state are assume to be $\hat{x}_0$, $\hat{P}_0$ respectively. In the above algorithms, K_k is the Kalman gain, $\hat{x}_k$ is the estimation state and $\hat{P}_k$ is the updated state noise covariance.

3.2. Proposed adaptive Kalman filter with gain correction (IRWE-AKFG)

To solve the divergent problems, adaptive Kalman filter (AKF) based on innovation or residual sequence have been proposed [17]. In AKF, Kalman gain is adjusted depending on the prior knowledge of the transmitted matrix, measurement matrix $\mathbf{H}$, process noise covariance matrix $\mathbf{Q}$ and measurement noise covariance matrix $\mathbf{R}$. The fixed values of measurement and process noise covariance matrices lead to give unreliable results, and hence, divergent occurs. In this section, Kalman gain is used to adjust the filter parameters based on the innovation sequence [31]. In AKF, innovation is the difference between the measurement value by the filter and its predicted value, which reflect the discrepancy between measurement quantity and system state prediction. The innovation of the Kalman filter is a theoretical zero-mean white noise sequence. Hence, the innovation can be used as a criterion to detect the divergence of the filter and to adapt the Kalman filter parameters [18–21].