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Robust adaptive filter allowing systematic model errors for transfer alignment

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ABSTRACT

This paper presents a new robust adaptive filtering method for transfer alignment by taking into account the systematic errors of observation and kinematic models in the filtering process. The proposed method overcomes the limitation of the traditional Kalman filter, that is, the requirement of precise kinematic and observation models for transfer alignment. It adaptively adjusts and updates the prior information through the equivalent weighting matrix and adaptive factor to resist the disturbances of systematic model errors on system state estimation, thus improving the accuracy of state parameter estimation. Experimental results and comparison analysis demonstrate that the proposed robust adaptive filtering method can effectively improve the performance of transfer alignment, and the achieved performance is much higher than those of the Kalman and traditional robust adaptive Kalman filters.

1. Introduction

In the context of delivering a military weapon such as a missile (referred to as the slave) from a moving or stationary base (referred to as the master), transfer alignment is defined as the process determining the orientation of the slave inertial navigation system (INS) according to the accurate information of the master INS [1,2]. As weapon systems require the quick response and high accuracy, rapidity and accuracy are always the objectives of transfer alignment.

The rapid transfer alignment is a velocity and attitude matching method to process host velocity and attitude information by using the Kalman filter to estimate the required information [3,4]. It can achieve the sub-milliradian alignment accuracy in a short time period even in the case of the wing-rock maneuver, without requirement of the lengthy-time lateral acceleration. It can also easily achieve the rapid alignment of SINS in the marine sway environment [5,6]. Therefore, rapid transfer alignment has been recognized as one of the most rapidest and accurate techniques for transfer alignment [1,4].

However, the use of the Kalman filter in rapid transfer alignment requires the accurate kinematic and observation models to achieve optimal estimation [7]. If deviations are involved in the ideal kinematic and observation models, the filtering solution will be biased or even divergent. Due to the various error sources in rapid transfer alignment, such as inertial sensor error, level arm effect, observation noise and carrier's flexure, it is unavoidable that the kinematic and observation models contain global or local systematic errors. Therefore, it is necessary to establish advanced filtering methods to accommodate the systematic errors of kinematic and observation models for improving the accuracy and stability of transfer alignment.

The use of robust estimation theories is a method to improve the robustness of the Kalman filter for rapid transfer alignment. Ali and Ushaq reported a robust Kalman filter by using the Huber's generalized maximum likelihood estimation theory to improve the robustness of the Kalman filter for INS transfer alignment [8]. Sun et al. improved the robustness of the Kalman filter using the hidden Markov model for INS transfer alignment [9]. However, these methods do not take into account systematic model errors in the filtering process, leading to the incapability to deal with random system noises.

The adaptive Kalman filter is a method to improve the estimation accuracy by adaptively adjusting and updating the prior information through the adaptive factor. Yu et al. reported an adaptive Kalman filter to estimate the misalignment angles under the circumstance that the model of wing flexure of an aircraft is unknown [10]. The adaptive filter does not require the priori knowledge of statistical characteristics of systematic noise, leading to the improved filtering accuracy in comparison with the standard Kalman filter. However, the adaptive Kalman filter has a poor sta-

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bility, especially in the presence of random errors [11,12]. It is also expensive in computational load.

The robust adaptive filtering is a method to deal with observation and system noises by robustly estimating the covariance matrix of observation noise and adaptively adjusting the covariance matrix of system state noise through the adaptive factor [13,14]. It cannot only augment additional parameters into the covariance matrix of predicted state vector obtained from the Kalman filtering model to compensate system noises, but it can also obtain reliable filtering results especially in the presence of abnormal observations by applying robust estimation principles to observation information. However, the existing methods on robust adaptive filtering mainly focus on the incorporation of robust estimation theories in the adaptive filtering process, without consideration of systematic model errors in the adaptive filtering process [12–16]. Further, these methods are dominated by integrated navigation system, while there has been very limited research focusing on using robust adaptive filtering for transfer alignment.

This paper presents a new robust adaptive filtering method for rapid transfer alignment. Unlike the existing robust adaptive filtering technique that incorporates robust estimation theories in the filtering process to deal with systematic errors, this method takes into account the systematic errors of kinematic and observation models directly in the filtering process to improve the accuracy of transfer alignment. This method adaptively adjusts and updates the prior information in the filtering process through the equivalent weighting matrix of observation vector and the adaptive factor to restrain the disturbances of abnormal observations and kinematic model's systematic error on state parameter estimation. The disturbance of abnormal observations is restrained by adaptively reducing the elements of the equivalent weighting matrix constructed from observation residuals. The adaptive factor is constructed from predicted residuals to control the utilization of predicted state information for state parameter estimation, thus restraining the disturbance of kinematic model error on system state estimation. The proposed filtering method not only accepts the systematic errors of kinematic and observation models, but it also reduces the alignment time by decreasing the size of the system state vector. Experiments and comparison analysis have been conducted to comprehensively evaluate the performance of the proposed methodology for transfer alignment.

2. Kinematic and observation models of transfer alignment

Assume that the navigation coordinate systems of both the master and slave SINSs are the E–N–U (East–North–Up) geographic coordinate system. The state vector is defined as

$$\mathbf{X}(t) = [\delta v_{\mathrm{E}}\ \delta v_{\mathrm{N}}\ \phi_{\mathrm{E}}\ \phi_{\mathrm{N}}\ \phi_{\mathrm{U}}\ \delta\varphi\ \delta\lambda\ \nabla_E\ \nabla_N\ \varepsilon_E\ \varepsilon_N\ \varepsilon_U]^{\mathrm{T}} \tag{1}$$

where $\mathbf{X}(t)$ is the system state vector; $(\delta v_{\mathrm{E}}, \delta v_{\mathrm{N}})$ is the velocity error between the master and slave SINSs; $(\phi_{\mathrm{E}}, \phi_{\mathrm{N}}, \phi_{\mathrm{U}})$ is the misalignment angle of the slave SINS; $\delta\varphi$ and $\delta\lambda$ are the longitude and latitude errors between the master and slave SINSs; (∇_E, ∇_N) is accelerometer's zero bias; and $(\varepsilon_E, \varepsilon_N, \varepsilon_U)$ is the gyro drift.

By taking into kinematic model's systematic error, the state equation of the transfer alignment system can be described as

$$\dot{\mathbf{X}}(t) = \mathbf{F}(t)\mathbf{X}(t) + \mathbf{W}(t) + \mathbf{D}(t)\mathbf{s}(t) \tag{2}$$

where $\mathbf{F}(t)$ is the state transition matrix, $\mathbf{W}(t) = [0_{1\times7}\ w_{\nabla_E}\ w_{\nabla_N}\ w_{\varepsilon_E}\ w_{\varepsilon_N}\ w_{\varepsilon_U}]^{\mathrm{T}}$ is the system state noise, which obeys $\mathbf{W}(t) \sim N(\mathbf{0}, \mathbf{\Sigma}_{\mathbf{W}_k})$, $\mathbf{D}(t)$ is the coefficient matrix of kinematic model's systematic error, and $\mathbf{s}(t)$ is kinematic model's systematic error with the priori value of zero.

Taking into account the deviation of observation, the observation equation of the transfer alignment system may be written as

$$\mathbf{Z}(t) = \mathbf{H}(t)\mathbf{X}(t) + \mathbf{V}(t) + \mathbf{G}(t)\mathbf{u}(t) \tag{3}$$

where $\mathbf{Z}(t)$ is the observation vector, $\mathbf{H}(t)$ the observation matrix, $\mathbf{V}(t) = [v_{\delta v_{\mathrm{E}}}\ v_{\delta v_N}\ v_{\Delta\theta}\ v_{\Delta\gamma}\ v_{\Delta\psi}]^{\mathrm{T}}$ the observation noise obeying $\mathbf{V}(t) \sim N(\mathbf{0}, \mathbf{\Sigma}_{\mathbf{V}_k})$, $\mathbf{u}(t)$ observation model's systematic error with the priori value of zero, and $\mathbf{G}(t)$ the coefficient matrix for the systematic error of the observation model.

Observation vector $\mathbf{Z}(t)$ is defined as the velocity error and misalignment angle between the master and slave SINSs

$$\mathbf{Z}(t) = [\delta v_E\ \delta v_N\ \Delta\theta\ \Delta\gamma\ \Delta\psi]^{\mathrm{T}} \tag{4}$$

where $(\Delta\theta, \Delta\gamma, \Delta\psi)$ is the attitude error between the master and slave SINSs.

By discretizing (1) and (3) at time t_k, the discrete kinematic and observation models of the transfer alignment system may be written as

$$\begin{cases} \mathbf{X}_k = \mathbf{\Phi}_{k,k-1}\mathbf{X}_{k-1} + \mathbf{W}_k + \mathbf{D}_{k,k-1}\mathbf{s}_k \\ \mathbf{Z}_k = \mathbf{H}_k\mathbf{X}_k + \mathbf{V}_k + \mathbf{G}_k\mathbf{u}_k \end{cases} \tag{5}$$

It is evident from (5) that systematic model errors $\mathbf{s}_k$ and $\mathbf{u}_k$ disturb the filtering process, leading to the biased or even divergent solution for transfer alignment. In fact, the traditional Kalman filter requires $E(\mathbf{W}_k) = 0$ and $E(\mathbf{V}_k) = 0$. However, due to the influence of systematic errors, this condition cannot be satisfied, that is [17],

$$\begin{cases} \mathbf{s}_k = E(\mathbf{W}_k) = E(\mathbf{X}_k - \mathbf{\Phi}_{k,k-1}\mathbf{X}_{k-1}) \neq 0 \\ \mathbf{u}_k = E(\mathbf{V}_k) = E(\mathbf{H}_k\mathbf{X}_k - \mathbf{Z}_k) \neq 0 \end{cases} \tag{6}$$

Therefore, in order to improve the accuracy of transfer alignment, it is necessary to consider in the filtering process the disturbances due to the systematic errors of the kinematic and observation models.

3. Filtering method

3.1. Analysis of systematic model errors

The predicted state vector at time t_k is

$$\bar{\mathbf{X}}_k = \mathbf{\Phi}_{k,k-1}\hat{\mathbf{X}}_{k-1} \tag{7}$$

where $\hat{\mathbf{X}}_{k-1}$ is the estimated state vector at time t_{k-1}.

The error equation for one-step predicted vector $\bar{\mathbf{X}}_k = \mathbf{\Phi}_{k,k-1}\hat{\mathbf{X}}_{k-1}$ of estimated state vector $\hat{\mathbf{X}}_{k-1}$ is

$$\mathbf{V}_{\bar{\mathbf{X}}_k} = \hat{\mathbf{X}}_k - \bar{\mathbf{X}}_k = \hat{\mathbf{X}}_k - \mathbf{\Phi}_{k,k-1}\hat{\mathbf{X}}_{k-1} \tag{8}$$

where $\mathbf{V}_{\bar{\mathbf{X}}_k}$ is the residual vector of predicted state vector.

Considering the estimate of the systematic error, the error equation for the state prediction from the kinematic model may be written as

$$\bar{\mathbf{V}}'_{\bar{\mathbf{X}}_k} = \hat{\mathbf{X}}_k - \mathbf{\Phi}_{k,k-1}\hat{\mathbf{X}}_{k-1} - \hat{\mathbf{s}}_k \tag{9}$$

where $\bar{\mathbf{V}}'_{\bar{\mathbf{X}}_k}$ is the residual vector of predicted state vector $\bar{\mathbf{X}}_k$ in the presence of the systematic error, which is called the predicted residual vector, and $\hat{\mathbf{s}}_k$ is the estimate of $\mathbf{s}_k$.

Accordingly, the error equation for the observation model is

$$\mathbf{V}_k = \mathbf{H}_k\hat{\mathbf{X}}_k - \mathbf{Z}_k \tag{10}$$

where $\mathbf{V}_k$ is the residual vector of the observation vector.

Considering the estimate of observation model's systematic error, the error equation for the observation model may be written as

$$\mathbf{V}'_k = \mathbf{H}_k\hat{\mathbf{X}}_k - \mathbf{Z}_k - \hat{\mathbf{u}}_k \tag{11}$$