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Efficient modeling of fiber optic gyroscope drift using improved EEMD and extreme learning machine

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ABSTRACT

In order to model the drift of fiber optic gyroscope (FOG) efficiently, a novel multi-scale prediction method is proposed by utilizing signal decomposition. Analytical expression of thermally induced drift of FOG is given first, which forms our theoretical basis of multi-scale prediction. Newly proposed bounded EEMD is used to decompose drift signal into a series of stationary modes, and then an adaptive feature selection criterion is proposed to construct distinct sub-series. Extreme learning machine is used to train these sub-series respectively, and a hybrid model is then obtained by adding up all the sub-models. Experiments have shown that, compared with the state-of-the-art methods, the proposed method improves prediction accuracy by two orders and achieves much faster speed in training process.

1. Introduction

Fiber optic gyroscope (FOG) is widely used in strap-down inertial navigation system (SINS), but the noise and drift contained in FOG can degrade the accuracy of SINS greatly over time without employing compensation methods. FOG senses the angular information based on the Sagnac effect which is caused by two beams of light that counter-propagate in a fiber optic [1]. Due to vibration and environment factors, such as temperature or diffusion of moisture, there are unbalanced stress and inhomogeneous thermal distribution existing in fiber-optic coil, which generates nonreciprocal phase shifts that have different properties [2]. In order to suppress these unwanted phase shifts, many methods have been proposed based on internal improvement of FOG structure, such as advanced winding method [3], accurate temperature control or adding accessories to isolate the disturbance. However, these hardware-based methods suppress drift at the cost of extra cost and bigger size. Due to non-ideal symmetric structure or temperature control error there is still residual error which is nonnegligible in navigation application. Besides, it is not always available for general users to access the internal structure of FOG. Mathematic-based methods provide more flexibility and are often easy to carry on, so compensation methods which are based on software and experiment data become an important complementary step of internal structure improvement.

Noise contained in FOG output possesses weak non-stationary and time-variant property, and the random noise would degrade modeling accuracy greatly without a pre-process of original drift. It is hard to predefine the model transformation of FOG precisely, which makes methods requiring entirety known system transformation less attractive. It has been reported that when the statistic property of noisy signal is unknown, wavelet-based denoising methods perform better than the other filtering methods [4]. However, it is tedious to select suitable decomposition parameters, and once the parameters are selected they will never change for the whole data series, which makes wavelet-based methods non-adaptive. Instead of wavelet transformation, empirical mode decomposition (EMD) is adopted here to decompose drift signal into multiple stationary sub-series that called intrinsic mode functions (IMFs) [5]. By combining the IMFs, a complicate signal can be divided into stochastic and deterministic parts, which can be used to improve the modeling and prediction process. However, in terms of identifying different parts of signal, there is still no robust mode selection criterion that is suitable for signal with different signal-to-noise ratio (SNR). A comparison between wavelet-based and EMD-based filtering methods has been made in previous study [6], and comparison results indicate that the latter performs better than the former, especially when SNR is small. Recently, EMD has been successfully used in processing FOG signal [7,8]. However, due to the inherent defect (e.g. mode mixing and end effect) much more work needs to be done. By applying noise assisted data analysis (NADA), an enhanced form of EMD named ensemble empirical mode decomposition (EEMD) was proposed to solve the

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mode mixing problem occurred in EMD [9]. However, EEMD destroys the data-driven property of EMD and produces spurious modes. We proposed a simplified EEMD named BEEMDAN in our previous work [10], where noise assisted decomposition was only used in the early stages of EMD. An analogous algorithm was proposed by employing NADA partly [11], where a threshold was empirical predefined to stop the ensemble decomposition, which, however, needs to be tested for more types of signal.

When FOG is used in harsh temperature environment, the temperature gradient vibration would generate random noise and drift. Furthermore, thermal conduct generated by the variant temperature inside fiber coil will certainly heat the coil in return. Generally, thermally induced drift can be mainly divided into two categories: (a) Shupe error caused by the radial direction temperature gradient variation of fiber coil (b) thermal stress-induced bias drift that depends on the average temperature of the fiber coil. Besides, it has also been reported that the temperature sensitivity of light components and electron drift in the detection and modulation circuit depend on temperature greatly. In a word, the final thermally induced drift is a hybrid of multiple sub-series characterized by different energies and frequencies, and the output of FOG includes the information of temperature variation. Most of current prediction methods assume that the thermally induced drift can be approximated by single model, such as polynomial model [12], neural network [13] and support vector machine [14], which are time-consuming or often unable to approximate the relation between temperature variation and drift signal.

A novel multi-scale prediction method is proposed to compensate the drift of FOG when ambient temperature varies dramatically. It is founded on the intuition that modeling stochastic and deterministic component of a signal respectively, would certainly reach a faster training speed and better prediction accuracy than global modeling. Here, BEEMDAN is used to decompose the drift signal to produce stationary IMFs, and then a robust mode selection criterion is proposed by utilizing self-similarity of the probability distribution function (PDF) of every IMFs. Finally, a newly developed fast learning method named extreme learning machine (ELM) [15] is applied to training each sub-series. The final prediction result is obtained by adding up all the output of sub-models trained by ELM, we named this method as multi-scale ELM (MS-ELM).

The rest of this paper is arranged as follows. A brief review of thermally induced FOG drift is given in Section 2. BEEMDAN algorithm and feature selection criterion are provided in Section 3. Multi-scale prediction method is presented in Section 4. And then, experiment is performed to verify MS-ELM. Finally, conclusions are drawn from the simulation results in Section 6.

2. Thermal induced errors

There are other nonreciprocal phase shifts that cannot be distinguished from rotation-induced phase shift in FOG output, which need an extra compensation process. The thermally induced drift mainly consists of two kinds of error, Shupe error due to thermal transients and thermal stress-induced bias drift from the fiber coating. Let the total length of waveguide be L, the phase shift due to measured rotation rate Ω and thermal fluctuations are [3]

$$\Delta\phi_R = \frac{2\pi LD}{\lambda c}\Omega, \tag{1}$$

$$\Delta\phi_E = \frac{\beta}{c}\cdot\frac{\partial n}{\partial \vartheta}\cdot\int_0^L \dot{\vartheta}(z,t)(L-2z)dz, \tag{2}$$

where D, c and λ are loop diameter, velocity and wavelength of light, respectively, $\beta = 2\pi/\lambda$ is the free space propagation constant, n denotes refractive index and $\partial n/\partial\vartheta$ is thermal-optic coefficient, $\dot{\vartheta}(z,t)$ is the temperature change rate at position z. The thermally induced nonreciprocal rotation error can be obtained by equating Eqs. (1) and (2),

$$\Omega_{E1} = \frac{1}{DL}\cdot n\frac{\partial n}{\partial\vartheta}\cdot\int_0^L \dot{\vartheta}(z,t)(L-2z)dz \tag{3}$$

Notice that, Shupe error has direct relation with thermal field change rate, and because $\Delta\phi_E(z) = -\Delta\phi_E(L-z)$, advanced symmetrical winding method can compensate the Shupe error to a great extent. However, due to unideal winding technology there is still residual error that degrades the precision of navigation a lot.

Thermal stress of fiber coating will also generate nonreciprocal phase shift, and the coefficient of thermal expansion must be very small to reduce this bias drift. The analytical expression of thermal stress induced error can be denoted as [16]

$$\Omega_{E2} = \frac{c}{DL}\int_0^L\left[\frac{2n\mu}{E_{core}} + \frac{n^3}{2E_{core}}(P_{11} - \mu P_{11} + P_{12} - 3\mu P_{12})\right] \times [E_{coating}\cdot\alpha_c\cdot\Delta T(t)]dz, \tag{4}$$

where E_{core} and μ denote Young's modulus and Poisson's ratio of fiber core, $E_{coating}$ and α_c are Young's modulus and thermal expansion coefficient of fiber coating. P_{11} and P_{12} denote photoelastic coefficients. Comparing Eq. (3) and Eq. (4), we can conclude that the inducements are different between Shupe error and bias drift, and it is hard to distinguish them in dynamic thermal transients. However, it is favorable to model them in different energy and frequency scales, which is also the main contribution of this paper.

3. Adaptive feature selection

Although modeling random drift using experiment data is effective and convenient, in order to compensate the drift error effectively, it is crucial to extract the weak drift features from heavy noisy FOG output. What's more, the phenomenon of Sagnac effect is very weak, which makes the output of FOG always submerged in noise, and degrades the short-term accuracy of SINS greatly. In a word, it is necessary to develop an adaptive filtering method to process FOG output and select useful features. In this section, we depict BEEMDAN in detail first, and then a new mode selection criterion is proposed.

3.1. Improved noise assisted decomposition

In the realization of EEMD, the assisted noise is added at the beginning of a complete EMD decomposition, and the final ensemble result is produced by averaging corresponding modes that generated at every stage. As there are maybe different numbers of modes generated in each trail, using a fixed denominator in averaging operation will certainly destroy the data-driven property of EMD. It has also been reported that the overlapping of added noise in EEMD produces spurious modes, and averaging mean envelope of each residue is better than averaging the noisy mode candidate [17]. EEMD utilizes the dyadic filter property of EMD of Gaussian noise to enhance the separation between different modes, but there is leakage of dyadic filter bank in the late stages of Gaussian noise decomposition [9]. Furthermore, as the added noise cannot be canceled in finite trails, the residual noise from NADA would destroy the data-driven property of mode extraction. In a word, using NADA partly not only retains the data-driven property of late obtained IMFs but also reduces the residual noise coming from NADA. What's more, it reduces the