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An EMD threshold de-noising method for inertial sensors

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ABSTRACT

Random errors of inertial sensors are key factors in influencing the performance of Inertial Navigation System (INS). Based on underlying white noise model, classical wavelet threshold de-noising method is incapable of eliminating colored noise. Since time-correlated colored noise is predominant, fractional Gaussian noise (fGn) is utilized to model sensor errors and the Hurst parameter of fGn is estimated by the periodogram method. Variances of the noise in Intrinsic Mode Functions (IMFs) decomposed by Empirical Mode Decomposition (EMD) are analyzed. The standard deviations of noise in the first tow IMFs are estimated by a robust estimator, and then the noise variances in other IMFs can be obtained after the variance relation among the IMFs decomposed from fGn is derived. Noise thresholds of IMFs are estimated through the obtained variances and an EMD threshold de-noising method using order-dependent thresholds is established. The method is firstly verified by a simulation example and then applied in INS and compared with wavelet de-noising method. Results show that wavelet threshold de-noising is poor at suppressing colored noise while EMD threshold de-noising is effective on reducing sensor errors due to its close association with proper noise model.

1. Introduction

Inertial Navigation System (INS) suffers from time-dependent error accumulation, causing a drift in the position, velocity and attitude (PVT) solution. The most remarkable issues that contribute to the performance degradation are random errors in inertial sensors, which cannot be effectively eliminated even by GNSS (Global Navigation Satellite System) and INS integration. How to effectively reduce these errors is of crucial importance for improving INS accuracy. Since the inertial data is considered to consist of actual vehicle motion and sensor noise, de-noising the inertial data could reduce the effects of random errors [15].

Digital low pass filter has been employed to remove the high frequency errors [8,20]. However, digital filter presents many deficiencies in analyzing signals with high temporal variation and/or well localized in time due to infinite support nature of Fourier basis waveforms (i.e. sine and cosine). Thus, the energy of such signals spreads on a high number of coefficients, which makes it hard to discriminate signals from a noisy background. Moreover, it has another disadvantage as it cannot filter the noise over the frequency band containing both actual signal and noise [18].

Wavelet de-noising is a widely-used tool, as wavelet is a time-frequency analysis method, especially suitable for investigating non-stationary signal. Given that wavelet coefficients at certain finest decomposition levels capture mostly noise, wavelet de-noising can simply be carried out by setting these coefficients to zero before the reconstruction process [16,15]. This approach endures the same disadvantage of the digital filter in that it cannot tackle the coefficients influenced both by actual motion and noise. In dynamic conditions, even coefficients at fine levels may contain the information of vehicle motion. Consequently, wavelet threshold method [4] is more feasible in most

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INS applications [5,2,19]. Classical wavelet threshold method operates well when the actual signal is affected by pure white noise. Under this assumption, noise contaminates all the wavelet coefficients equally [4] and a universal threshold can be easily determined. However, there are a large amount of colored noise components in inertial sensors such as bias instability, rate random walk and Markov process. They jeopardize more than white noise, especially in low-cost sensors. Without comprehensive investigation for the characteristic of sensor errors, current wavelet threshold method applied in inertial data actually performs de-noising on the basis of white noise model, lacking theoretical stringency. Nassar and El-Sheimy [17] combined INS error modeling using Autoregressive (AR) process and wavelet de-noising in the framework of INS/GPS navigation. AR process is used to model the colored component in the inertial errors. Normally, de-noising will be combined with error modeling in Kalman filtering to totally eliminate the noise. But we want to explore the effects of de-noising in the framework of navigation by INS only.

Empirical Mode Decomposition (EMD) has been pioneered by Huang et al. [9] for adaptively decomposing signals into a sum of "well-behaved" AM–FM components consisting of natural "intrinsic" building blocks, termed Intrinsic Mode Functions (IMFs). Eliminating a certain number of low order IMFs with relatively high frequencies naturally reduces the influence of noise [7,13]. This conventional EMD de-noising method needs to know whether a specific IMF contains useful information or primarily noise. Actually, many IMFs contain both useful components and noise, especially in dynamic conditions. Thresholding is a more flexible de-noising scheme, with some preliminary results already published [1,14], where the wavelet thresholding was directly applied to the EMD case without further consideration of the noise property of IMFs. Kopsinis and Mclaughlin developed an EMD-based threshold de-noising method inspired by wavelet thresholding (2009). They utilized order-dependent thresholds; in addition, EMD interval thresholding is used to replace direct EMD thresholding which causes severe discontinuities to thresholded IMFs. However, the problem of colored noise has not been discussed.

This paper proposes a novel EMD threshold de-noising method based on fractional Gaussian noise model for inertial sensors. The rest of this paper is structured as follows. Section 2 gives a brief review to the EMD method. In Section 3, fractional Gaussian noise with Hurst parameter is introduced as the model of inertial sensor errors to characterize the influence of time-correlated colored noise. The periodogram method for estimating Hurst parameter is given. Section 4 presents the proposed order-dependent EMD threshold de-noising method. Based on the fractional Gaussian noise model of sensor errors, variance of the noise in each IMF is derived and noise thresholds of IMFs are estimated through the obtained variances. In Section 5, results and analysis of the proposed method applied in the de-noising of both simulation signals and field dynamic inertial data are presented. Section 6 concludes the work done.

2. Brief review of EMD

EMD adaptively decomposes a multicomponent signal into several IMFs. An IMF is defined as a function that must satisfy two conditions [9]: (1) in the whole dataset, the number of extrema and the number of zero crossings must either equal or differ at most by one; (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD method is based on the local characteristic time scale instead of the average time scale, so the instantaneous frequency has physical meaning. Moreover, it is a fully data-driven method.

For a given signal $x(t)$, the sifting process of extracting IMFs involves following steps [9]:

(1) Identify all the local extrema of the signal, and then connect all the local maxima by a cubic spline line to produce the upper envelope. Repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. Their mean is designated as m_1, and the difference between the data and m_1 is the first component:

$$h_1 = x(t) - m_1 \tag{1}$$

(2) Ideally, h_1 should satisfy the definition of an IMF, however, the shifting process has to be repeated as many times as necessary to eliminate all the riding waves. In the subsequent steps, h_1 is treated as the data. Then,

$$h_{11} = h_1 - m_{11} \tag{2}$$

This process can be repeated up to k times:

$$h_{1k} = h_{1(k-1)} - m_{1k} \tag{3}$$

Thus, we obtain the first IMF:

$$imf_1 = h_{1k} \tag{4}$$

(3) Calculate the residue:

$$r_1 = x(t) - imf_1 \tag{5}$$

Iterate on the residue to obtain other IMFs.

The approximate local envelope symmetry condition in the sifting process is called the stoppage criterion. The most widely used criterion is a Cauchy type of convergence test which has been comprehensively described by Huang et al. [9].

The decomposition process finally stops when the residue r_n becomes a monotonic function or a function with only one extremum from which no more IMF can be extracted. After the decomposition, $x(t)$ is decomposed into several IMFs and a residue:

$$x(t) = \sum_{i=1}^{n} imf_i + r_n \tag{6}$$

By construction, each IMF is a zero-mean waveform whose number of zero-crossings differs at most by one from the number of its extrema. The number of these