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Gross errors identification and correction of in-vehicle MEMS gyroscope based on time series analysis

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Abstract: This paper presents a novel approach to identify and correct the gross errors in the microelectromechanical system (MEMS) gyroscope used in ground vehicles by means of time series analysis. According to the characteristics of autocorrelation function (ACF) and partial autocorrelation function (PACF), an autoregressive integrated moving average (ARIMA) model is roughly constructed. The rough model is optimized by combining with Akaike's information criterion (AIC), and the parameters are estimated based on the least squares algorithm. After validation testing, the model is utilized to forecast the next output on the basis of the previous measurement. When the difference between the measurement and its prediction exceeds the defined threshold, the measurement is identified as a gross error and remedied by its prediction. A case study on the yaw rate is performed to illustrate the developed algorithm. Experimental results demonstrate that the proposed approach can effectively distinguish gross errors and make some reasonable remedies.

Key words: microelectromechanical system (MEMS) gyroscope; autoregressive integrated moving average (ARIMA) model; time series analysis; gross errors

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In order to cope with the GPS failure within high-building areas, culverts and mountain valleys, the vehicle integrated navigation based on multi-sensors has been developed rapidly in recent years[1-4]. As one of the key sensors in the integrated navigation system, the gyroscope is extensively studied by plenty of companies and research institutes, leading to a drastic improvement in stability and reliability. The novel MEMS gyroscope, with the advantages of low cost, compact size, light weight and high reliability, has obtained a broad application in vehicle integrated navigation and automotive testing[5-6]. However, due to MEMS fabrication imperfections and environmental variations, the current MEMS gyroscope is always subject to white noise and constant drift random errors[7]. In addition, the abnormal data will inevitably contaminate MEMS gyroscope output because it is susceptible to vibration, temperature changes and other external factors during the running of the vehicle. Therefore, for the purpose of eliminating the adverse effects on subsequent multi-sensor fusion and test results, it is of great importance to distinguish the gross errors and correct them reasonably.

Traditionally, there are four most common rules to identify gross errors, i. e., the 3δ criterion, the Grubbs criterion, the Chauvenet criterion and the Dixon criterion[8-9]. If the specific critical factors and confidence levels are not considered, the algorithms of these four criteria can be described as follows: First, it is required to calculate the mean $\bar{x}$ and standard deviation δ according to the original data $X_1, X_2, \ldots, X_n$. If $|X_i - \bar{x}| > k\delta$, X_i is thought to be a gross error and replaced with the average or median of several data around X_i. Obviously, the aforementioned $\bar{x}$ and δ have already been contaminated by potential gross errors in the process, frequently leading to misjudgments in some special cases. Besides, these methods purely tackle gross errors in the view of data processing without referring to the system and error characteristics, leading to poor performance when applied to the MEMS gyroscope. Meanwhile, the gross error identification and correction of an in-vehicle MEMS gyroscope remain open for research and the related literature is rare to the best knowledge of the authors.

In view of this, a novel approach based on time series analysis is introduced to identify and correct the gross errors of MEMS gyroscopes. When the difference between the measurement and its prediction calculated using the optimal model exceeds the defined threshold, the measurement is deemed as a gross error and remedied with the help of its prediction. Experimental results show that the proposed algorithm can achieve a high performance.

1 Time Series Analysis Models

1.1 ARMA model

The common method of modeling time series is to construct an autoregressive moving average process (ARMA). Theoretically, this model derives from the autocorrelation analysis of time series, which not only involves various degrees of correlations over time for inertial sys-

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tems, but also considers the random interferences, accordingly gaining high accuracy for short-term predictions[10-11].

It should be emphasized that the time series must be generated by a zero-mean stationary random process when modeling by the ARMA model. Therefore, the necessary statistical tests should be carried out in advance to ensure the raw data suitable for further analysis.

1.2 ARIMA model

In the actual application, the vast majority of the time series are definitely non-stationary. For the sake of modeling this kind of time series, Box and Jenkins brought forward the autoregressive integrated moving average (ARIMA) model. Generally speaking, ARIMA (p, d, q) consists of AR (p), MA (q), and ARMA (p, q) models. In the context of this approach, the non-stationary series are required to perform d times differences until they transform into a stationary series before applying ARMA (p, q) [12].

ARMA (p, q) is the most widely used model in the field of time series analysis. For a zero-mean stationary series $y(k)(k=1, 2, \ldots, n)$ with variance δ^2, it is referred to as an ARMA (p, q) model if it can be expressed as

$$y(k) = \phi_1 y(k-1) + \phi_2 y(k-2) + \ldots + \phi_p y(k-p) + \varepsilon(k) - \theta_1 \varepsilon(k-1) - \theta_2 \varepsilon(k-2) - \ldots - \theta_q \varepsilon(k-q) \tag{1}$$

where $\phi_1, \phi_2, \ldots, \phi_p$ and $\theta_1, \theta_2, \ldots, \theta_q$ are parameters of autoregressive component and the moving average component, respectively; $\varepsilon(k)$, $\varepsilon(k-1)$, …, $\varepsilon(k-q)$ are Gaussian white noise series with mean zero and variance δ^2. In addition, the AR (p) and MA (q) models can be viewed as special variants of ARMA (p, q) when the parameter $p=0$ or $q=0$.

2 Method

The approach proposed in this paper can be summarized as the following procedures.

2.1 Checking stationarity

As mentioned above, stationarity is the basic requirement when applying the ARMA (p, q) model to a time series. There are several methods which account for whether a series is stationary or not. The most popular is the augmented Dickey-Fuller test (ADF), which is applied to test the stationarity of the yaw rate series in this paper. According to Box and Jenkins, if a time series is not stationary, this time series need to be differentiated before utilizing ARMA (p, q).

2.2 Identifying ARMA (p, q) model

Identification of models usually relies on the analysis of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). While the autocorrelation function measures the correlation between values in a time series separated by N, which represents the number of lags between these data, the partial autocorrelation function provides an indication in determining the number of lags in the AR model. Tab. 1 summarizes a rough guideline for initial model identification.

Tab. 1 Model identification using ACF and PACF

Type	AR(p)	MA(q)	ARMA(p, q)
ACF	Tails off	Cuts off after lag q	Tails off
PACF	Cuts off after lag p	Tails off	Tails off

With the help of ACF and PACF, both p and q can be roughly acquired. However, in most cases, more than one model will be accepted by the rule. To choose the best one to describe the raw data, model comparison is usually examined by Akaike's information criterion (AIC). The AIC rule serves as a criterion for assessing the goodness of model fitting, and a smaller AIC value normally corresponds to a better model fitting for a given series. In addition, high order models are discouraged.

2.3 Estimating parameters

In this paper, the least squares algorithm is introduced to estimate ϕ_1, ϕ_2, …, ϕ_p and θ_1, θ_2, …, θ_q.

2.4 Diagnosing models

In order to test whether the selected model fits the data well, it is necessary to diagnose the model. If the model fits well, the residuals of the model should behave as white noise, otherwise the model needs to be improved. The residual ACF and PACF are tools for model diagnostic checking. If the residual ACF and PACF indicate no significant spikes, the chosen model is in goodness of model fitting.

2.5 Gross errors identification and correction

After the above steps, an appropriate model ARIMA (p, d, q) is constructed and used to tackle gross errors. Suppose that the obtained ARIMA (p, d, q) model can be expressed as

$$\hat{y}(k) = \phi_1 y(k-1) + \phi_2 y(k-2) + \ldots + \phi_p y(k-p) + \varepsilon(k) - \theta_1 \varepsilon(k-1) - \theta_2 \varepsilon(k-2) - \ldots - \theta_q \varepsilon(k-q) \tag{2}$$

where $\hat{y}(k)$ is the predication of $y(k)$. If $|\hat{y}(k) - y(k)| \geqslant \theta$, $y(k)$ is identified as abnormal data and replaced by the median of $\hat{y}(k-p)$, $\hat{y}(k-p+1)$, …, $\hat{y}(k)$. For the application in the yaw rate, the threshold θ is set to be 3 rad/s.

3 Case Study

In order to verify the proposed approach, the yaw rate data collected by the ZX-VG MEMS gyroscope is studied in this paper.

Fig. 1 describes the original data $y(k)$ ($k = 1, 2, \ldots, 20\ 000$) with a sampling interval of 20 ms. From Fig. 1, it is obvious that the data has significant increasing trends at certain stages, which will cause inevitable non-stationarity.

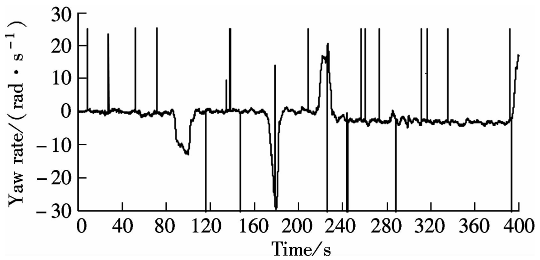

Fig. 1 Original yaw rate data

In order to facilitate modeling, the first 400 data, namely $y(t)$ ($t = 1, 2, \ldots, 400$), are chosen as a sample to research. According to Box and Jenkins, the preliminary difference should be performed as

$$x(t) = y(t+1) - y(t) \tag{3}$$

Afterwards, the ADF test is used to check the process stationarity and the results are shown in Tab. 2. The null hypothesis is that the series has a unit root. In Tab. 2, $-3.814\ 591$, $-3.082\ 001$ and $-2.716\ 303$ are the test critical values under the significance level of 1%, 5% and 10%, respectively. The augmented Dickey-Fuller test statistic is $-4.305\ 675$, which is lower than the critical value under the significance level of 1%. Therefore, the null hypothesis is rejected and the series $x(t)$ is stationary. The mean value of $x(t)$ is $-0.000\ 172$, so $x(t)$ approximates a zero-mean sequence.

Tab. 2 Stationarity test

The level of test	t	P
ADF	−4.305 675	0.029 0
1%	−3.814 591	
5%	−3.082 001	
10%	−2.716 303	

After obtaining the zero-mean stationary series, the next step is to identify the ARMA (p, q) model. As mentioned above, time series modeling is based on extracting information from ACF and PACF. The ACF and PACF of $x(t)$ are plotted in Fig. 2. As shown in Fig. 2, the ACF exceeding the confidence interval occurs in the first lag, whereas the PACF occurs in the first two lags. Accordingly, the candidate models are ARMA (1, 1) and ARMA (2, 1) for estimation. In light of the AIC rule, the model ARMA (1, 1) gains the smaller AIC value, and it is chosen as the best fitted model for data interpretation.

By means of the least squares algorithm, the parameters ϕ_1 and θ_1 are calculated and they are equal to $-0.224\ 8$ and $-0.449\ 7$, respectively. Namely, the selected ARMA (1, 1) is

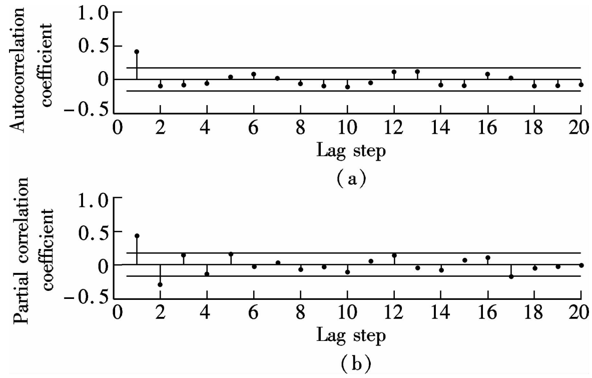

Fig. 2 The ACF and PACF of $x(t)$. (a) ACF; (b) PACF

$$x(t) = -0.224\ 8x(t-1) + \varepsilon(t) + 0.449\ 7\varepsilon(t-1) \tag{4}$$

where $\varepsilon(t)$ and $\varepsilon(t-1)$ are the Gaussian white noise series with mean zero and variance 0.002 4, i. e., the same as $x(t)$.

In order to examine whether the selected model fits the data well, it is necessary to diagnose the model. Define residual $r(t)$ as

$$r(t) = \hat{x}(t) - x(t) \tag{5}$$

The ACF and PACF of residual $r(t)$ are shown in Fig. 3. As illustrated in Fig. 3, the residual ACF and PACF indicate no significant spikes, which means that the ARMA(1, 1) is in goodness of model fitting.

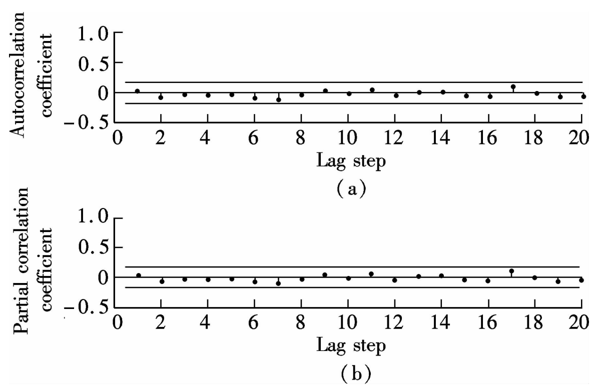

Fig. 3 The ACF and PACF of residual. (a) ACF; (b) PACF

Finally, replacing $x(t)$ with Eq. (3), the ARIMA(1, 1, 1) model of $y(k)$ can be obtained as

$$y(k+1) = 0.775\ 2y(k) + 0.224\ 8y(k-1) + \varepsilon(k) + 0.449\ 7\varepsilon(k-1) \tag{6}$$

Then, it can be utilized to identify and correct the gross errors of the yaw rate. Initially, this paper assumes $\hat{y}(k)$ as the prediction of $y(k)$ and set $\hat{y}(1) = y(1)$, $\hat{y}(2) = y(2)$. Starting from $k = 2$, $y(m-1)$, $y(m)$ and $y(m+1)$ are extracted from $y(k)$ in order every time. According to Eq. (6), $\hat{y}(m+1)$ can be written as

$$\hat{y}(m+1)=0.775\,2y(m)+0.224\,8y(m-1)+\varepsilon(m)+0.449\,7\varepsilon(m-1) \tag{7}$$

If $|\hat{y}(m)-y(m)|\geqslant 3$ rad/s, $y(m)$ is identified as abnormal data and replaced by the median of $\hat{y}(m-1)$, $\hat{y}(m)$ and $\hat{y}(m+1)$. The corrected yaw rate and original data are shown in Fig. 4.

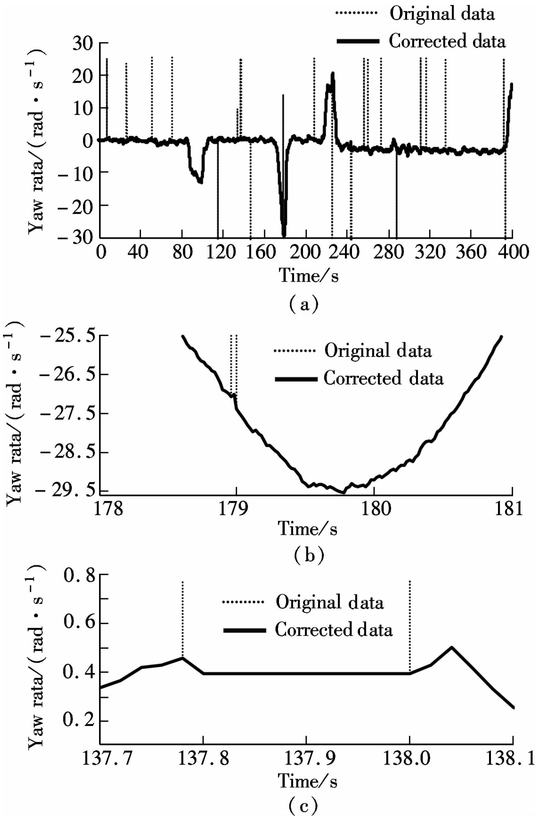

Fig. 4 Comparison of original data and corrected data. (a) The general drawing; (b) Partial enlarged detail of the general drawing with one gross error; (c) Partial enlarged detail of the general drawing with ten successive gross errors

Fig. 4 reveals that the approach proposed in this paper can effectively distinguish the gross errors and correct them reasonably. According to Figs. 4(b) and (c), the method is not only suitable for one gross error but also for successive gross errors.

4 Conclusion

This paper proposes a novel approach to identify and amend the gross errors of an in-vehicle MEMS gyroscope based on time series analysis. The optimal ARIMA model is constructed combined with AIC and the analysis of ACF and PACF. Through analyzing the case of the yaw rate, the application of time model analysis is appropriate and performs very well, which demonstrates that the proposed method is suitable for gross error identification and correction.

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基于时间序列分析的车载 MEMS 陀螺仪异常测量数据的辨识与修正

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摘要:针对目前车载 MEMS 陀螺仪含有较多异常测量数据的情况,提出了一种基于时间序列分析的辨识和修正方法. 根据 MEMS 陀螺仪测量数据的自相关函数和偏相关函数特征初步确定自回归移动平均(ARIMA)模型,再引入 AIC 准则确定最优模型,并采用最小二乘估计法对模型参数进行估计. 当此模型的有效性检验通过时,即用该模型对测量数据的变化趋势进行预测. 当某个测量值与其预测值之差大于设定的阈值时,则判定此测量值为异常数据并用预测值进行修正. 为了验证所提算法的效果,对 MEMS 陀螺仪测量的横摆角速度数据进行了实验. 结果表明,所提方法可以有效地识别出车载 MEMS 陀螺仪的异常测量数据,并能进行合理的修正.

关键词:MEMS 陀螺仪;ARIMA 模型;时间序列分析;粗大误差

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