

A real-time data processing method based on twice weighted improved Kalman filter algorithm

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Abstract. The data obtained by sensor is strong randomness and deviates from Gaussian distribution. The Extended Kalman Filter (EKF) is cost-effective and easy to cause large errors while processing data. At the same time, the accuracy of the data prediction is not high enough. Therefore, an improved filter based on the original EKF is proposed to improve the prediction accuracy and noise reduction effect in this paper, which combines the predicted value and the measured value of the EKF twice to find the root mean square to obtain a more accurate predicted value. The noise reduction effect of EKF and TWEKF is compared by using MATLAB. And the root means square error (RMSE), signal-to-noise ratio (SNR), smoothness (S) and other quantitative judgment indexes prove that TWEKF has better noise reduction effect than EKF.

Keywords: Twice Weighted Extended Kalman Filter (TWEKF), Extended Kalman Filter (EKF), Data preprocessing.

1. Introduction

With the rapid development of the intelligent era, real-time data preprocessing technology is playing an increasingly important role in automated factories and intelligent homes. Manufacturing companies have become more and more sensitive to the progress of smart products and become more transparent. Many companies are developing unmanned factories, and residential home's appliances are moving towards intelligence [1]. However, the conditions in the workshops of manufacturing companies are complex and unpredictable, which leads to increased difficulty in unmanned factories. Lots of households and many types of smart-home's appliances resulted the smart devices cannot accurately capture the working conditions of smart-home 'appliances. When the data processing method is not perfect enough, it will face problems such as mistakes in factory production decision-making and insufficient intelligence of household appliances. There is a conflict between real-time requirements and the lag of data processing. Therefore, the preprocessing method of real-time data has become a key technology that needs to be broken through in the intelligent era. The arrival of autonomous driving technology also requires the use of real-time data processing, a vital technology. During the process of automatic driving, the vehicle needs to detect its real-time working status, process the collected data and feed it back to the driving vehicle, so that the vehicle can correct the driving status in time.

The measured value of any sensor has a certain error. The error is accompanied by various reasons, not only the measurement error of the device itself but also the aging of the device and the converter during the use of the sensor. And the signal transmission process is subject to some interference, resulting in random errors in the measured data. Compared with other traditional filters, the Kalman filter has the most significant advantage in that it can remove random errors in the system. However, the traditional Kalman Filter (KF) can only be used for linear systems and has certain limitations. Although EKF can be applied to non-linear systems, the application range is increased. However, some errors are generated during the linearization process, and these errors cause the filter to diverge

if the initial state estimation is not accurate enough [2]. The above two filtering methods have a certain degree of deviation in prediction accuracy.

In order to further improve the prediction accuracy, an improved EKF method proposed. Therefore, the complete algorithm of the TWEKF is further derived from the EKF algorithm. In the update step of EKF, the predicted value obtained in the prediction step is combined with the observed value twice to obtain the root mean square. Chapter 2 shows the derivation process of the complete algorithm of the EKF. Chapter 3 introduces the evaluation index of filtering noise reduction effect. Chapter 4 uses MATLAB to conduct experiments on three sets of simulation data. Chapter 5 uses two filters to reduce the noise of the three sets of data measured on the vehicle transmission test bench. The conclusion is summarized in Chapter 6.

2. Improved extended kalman filter algorithm based on twice weighting

The EKF is an extension of the KF and has a wider application range than the KF. By superimposing the Taylor expansion term, the highest term of the first-order Taylor formula is dropped. Then the nonlinear system is linearized and substituted into the KF algorithm, which leads to the EKF algorithm. The TWEKF proposed in this article is an improved algorithm based on EKF. It further combines the one-step predicted value of the EKF algorithm with the observed value to find the root mean square of the two. And use this value as a new one-step predicted value, making the combination of predicted value and observed value closer.

The state equation and measurement equation of the EKF is:

$$x_{k+1} = f(x_k) + W_k \quad (1)$$

$$Z_k = h(x_k) + V_k \quad (2)$$

Here, formulas (1) and (2) are expanded by Taylor and the highest term is discarded:

$$x_{k+1} = F_k x_k + f(\hat{x}_k) - F_k \hat{x}_k + W_k \quad (3)$$

$$Z_k = H_k x_k + h(\hat{x}_k) - H_k \hat{x}_k + V_k \quad (4)$$

Among them, Z_k is the observation value, W_k and V_k are process noise and observation noise. And the covariance is Q_k and R_k . The state transition matrix F_k and the observation matrix H_k are Jacobian matrices of f and h .

$$F_k = \frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \dots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \quad (5)$$

$$H_k = \frac{\partial h}{\partial x} = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \dots & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \dots & \frac{\partial h_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_n}{\partial x_1} & \frac{\partial h_n}{\partial x_2} & \dots & \frac{\partial h_n}{\partial x_n} \end{bmatrix} \quad (6)$$

One-step state prediction:

$$\hat{x}_{k/k-1} = f(x_{k-1/k-1}) \quad (7)$$

Optimal state estimation:

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k [Z_k + h(\hat{x}_{k/k-1})] \quad (8)$$

To make the one-step prediction and the observation value more closely integrated, to find the root mean square of the two, the formula (8) can be expressed as the formula (9):

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k [Z_k + \sqrt{h^2(\hat{x}_{k/k-1}) + Z_k^2}] \quad (9)$$

Kalman gain:

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R_{k-1})^{-1} \quad (10)$$

Forecast mean-square-error:

$$P_{k/k-1} = F_{k-1} P_{k-1/k-1} F_{k-1}^T + Q_{k-1} \quad (11)$$

Estimated mean-square-error:

$$P_{k/k} = (I - K_k H_k) P_{k/k-1} \quad (12)$$

The TWEKF's process is shown in Fig. 1: Input the initial state value of the filter; Perform one-step state prediction; calculate its prediction variance; Calculate the optimal estimate of the TWEKF recursively according to the observation value at time k; Get the gain of the TWEKF; Be ready to estimate the variance for the next forecast.

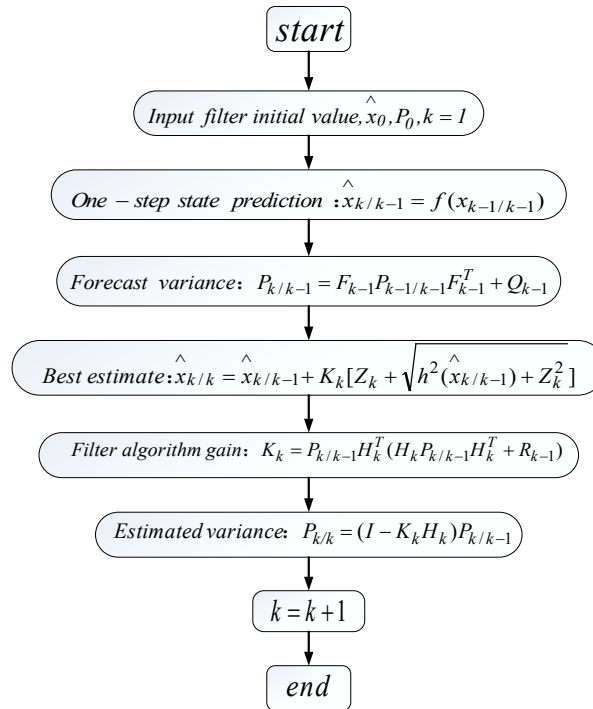


Figure 1. Flow chart of the TWEKF

3. Noise reduction effect evaluation index

To verify the superiority of the TWEKF processing data, simulation and experiment methods were used for analysis. The noise reduction effect of the two filtering methods is judged by comparing the three evaluation indexes of SNR, RMSE and S.

SNR: It is the ratio of the original signal energy to the noise energy. It is generally believed that the higher the SNR-value, the better the filtering effect. Calculated as follows:

$$SNR = 10 \times \lg \left(\frac{\sum_{k=1}^n x_k^2}{\sum_{k=1}^n (x_k - \hat{x}_k)^2} \right) \quad (13)$$

RMSE: Its value is the root mean square error between the filtered signal and the original signal. Its value is negatively related to the noise reduction effect of the filter.

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (x_k - \hat{x}_k)^2} \quad (14)$$

The S reflects the smoothness of the filtering result. The value of smoothness is also negatively related to the performance of the filter.

$$S = std(\frac{\hat{x}_k - \hat{x}_{k-1}}{\Delta_t}) \quad (15)$$

Among them, std is the standard deviation calculation, Δ_t is the sampling interval, and $\hat{x}_k$ is the filtering result.

4. Simulation and analysis

The simulation uses three sets of data randomly collected by the displacement sensor as the processing object. The model of the displacement sensor is GT2-P12, produced by Keyence. The collected data uses two kinds of filters to reduce noise in the matlab environment. The time step is set to one second and the length N to 20000. Finally, draw a comparison chart of the noise reduction effect of the two filtering results, and calculate the evaluation parameters.

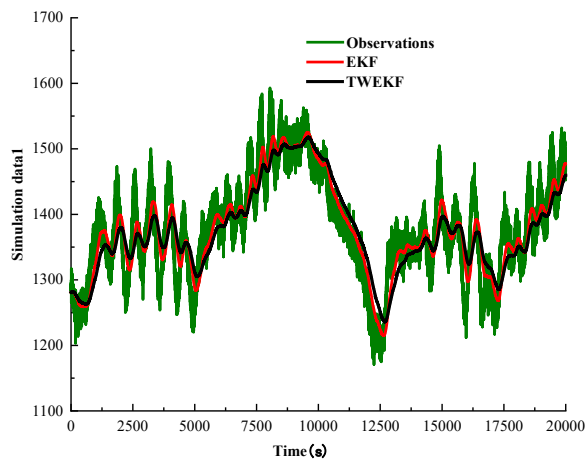


Figure 2. Simulation data1 filter graph

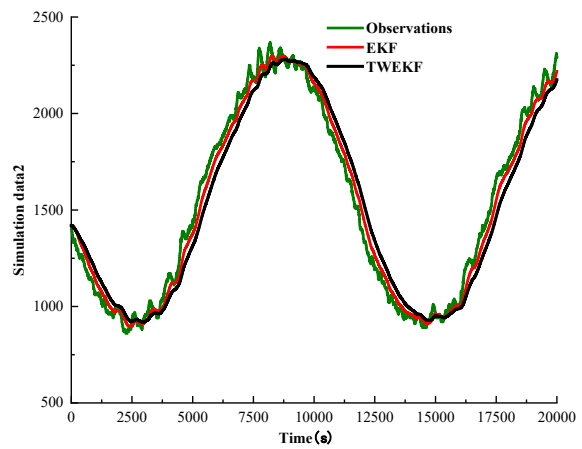


Figure 3. Simulation data2 filter graph

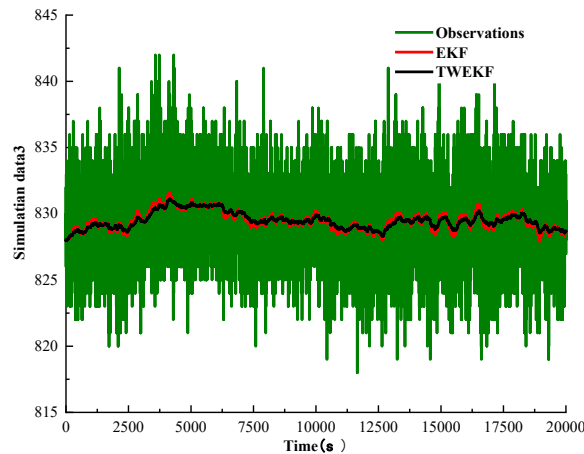


Figure 4. Simulation data3 filter graph

The simulation results is shown in Fig 2, 3 and 4. The three lines respectively represent the original observation value measured by the displacement sensor, and the data after the EKF and the TWEKF noise reduction. It can be seen from the figure that the distribution rules of the three sets of data measured by the sensor are completely different, which satisfies the randomness of the simulation to a certain extent. The first set of data has relatively strong randomness, large amplitude, and no obvious law. The second has the characteristics of sinusoidal distribution. The third group of data has a small amplitude, and the original data image looks relatively dense. The three sets of original data are processed by two filtering methods, the resulting data images can fit the original data images better.

This also reflects that the two filtering methods are applicable to various complex types of data. The regularity or irregularity of each set of data does not affect the processing results.

Table 1. Evaluation parameters of filtering simulation data

Simulation data	Filtering method	Evaluation parameters		
		<i>RMSE</i>	<i>SNR</i>	<i>s</i>
Date1	EKF	69.4320	31.5238	0.1845
	TWEKF	65.4084	29.8616	0.1111
Date2	EKF	481.6985	28.8230	0.2878
	TWEKF	470.3310	23.7075	0.2586
Date3	EKF	0.6924	50.3369	0.0127
	TWEKF	0.6149	502548	0.0064

Comprehensive comparison of the three filter evaluation parameter values gained by EKF and TWEKF, SNR of the three sets of data filtering results is close numerically. And the SNR has reached a certain numerical standard. It illustrates that the two filtering methods have achieved certain effect in reducing noise. The RMSE Processed by TWEKF are 65.4048, 470.3310 and 0.6149, respectively, which are 5.8%, 2.4% and 11.2% lower than the EKF processing. The S after TWEKF treatment was 39.8%, 10.1% and 49.6% lower than that EKF treatment, respectively. The above data shows that compared with EKF, TWEKF can get a more perfect optimal estimate than EKF. At the same time, the smoothness of the results achieved by the TWEKF is also better than that of the EKF. Therefore, the proposed TWEKF method has the same function of EKF in data processing. And compared with the EKF, the TWEKF has greater noise reduction effect in processing data.

5. Experiment and analysis

In order to further verify the effectiveness of the improved filtering process data, Two filtering methods are used to process the data. The data is measured by the vehicle transmission test bench, and three representative data groups of turbine speed, slave Speed and forward gear pressure are selected as the processed objects. For better comparison of simulation and experimental results, the data capacity of each group of experiments is 20,000.



Figure 5. Real-time data processing verification of vehicle transmission

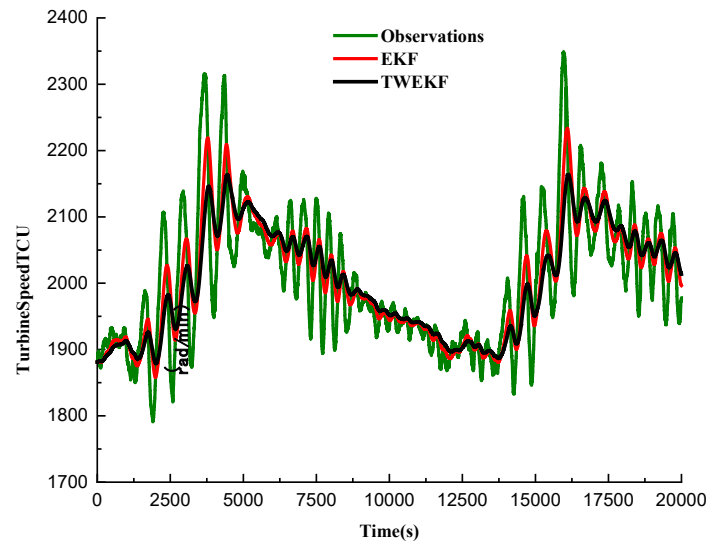


Figure 6. Filtering graph of actual experimental turbine speed

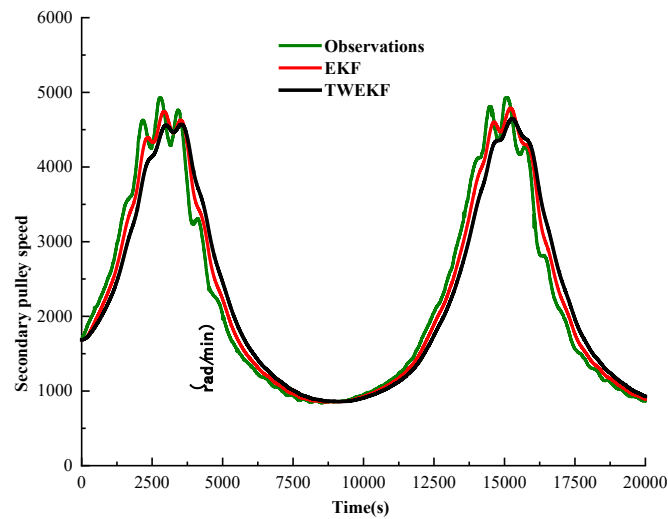


Figure 7. Filtering graph of driven wheel speed in measured experiment

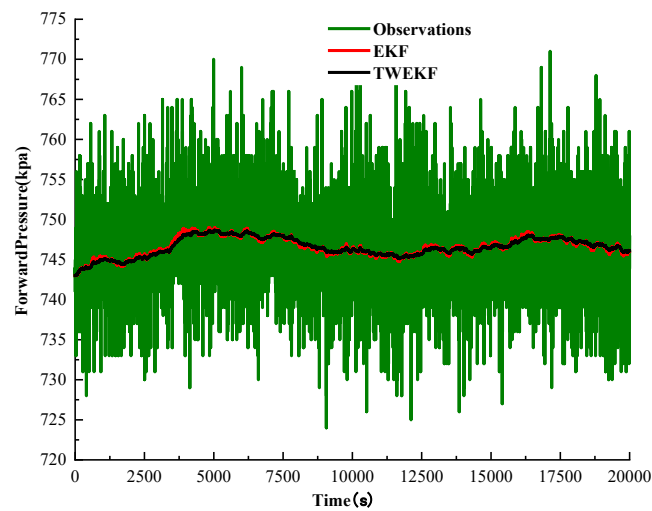


Figure 8. Filtering graph of forward gear pressure of actual test experiment

Table 2. Evaluation parameters of filter measured data

Experimental data	Filtering method	Evaluation parameters		
		<i>RMSE</i>	<i>SNR</i>	<i>S</i>
Turbine Speed	EKF	85.0866	30.5954	0.2993
	TWEKF	79.7309	29.5098	0.1679
Secondary pulley Speed	EKF	1306.4	22.2233	1.0250
	TWEKF	1261.8	17.2962	0.9078
Forward Pressure	EKF	1.2063	46.6178	0.0174
	TWEKF	1.1764	46.5566	0.0088

From the three images, it can be seen that the contours of the data image processed by the two filtering methods are roughly the same, which further verifies that the TWEKF has the same effect as EKF in data processing. From the evaluation result indicators in Table II, the conclusion by the two filter processing methods on the three sets of data are basically consistent with the processing results obtained in the simulation. The SNR of the obtained filtering results are not much different and reach a certain standard. The RMSE and S of the processing results of the TWEKF method are smaller than the RMSE and smoothness obtained by the EKF method. The experimental results show that the RMSE of TWEKF is reduced by 6.3%, 3.4%, and 2.5%, respectively, compared with the one by EKF method. Compared with the S treated by TWEKF and the treated by EKF, it decreased from 80.2993, 1.0250, 0.0174 to 0.1679, 0.9078, 0.0088, respectively.

6. Conclusion

Aiming at the insufficient combination of the prediction- step and the observation value in EKF, this paper proposes the EKF improve the EKF. TWEKF uses the twice weighted root mean square of predictive value and Observation as the new one-step prediction value to achieve a more accurate prediction value. The simulation results show that the RMSE of the three sets of data processed by TWEKF is reduced by 5.8%, 2.4% and 11.2%, respectively, and the smoothness value has dropped by 39.8%, 10.1% and 49.6% respectively. The three sets of data in the experimental results are processed by the TWEKF and the RMSE is reduced by 6.3%, 3.4%, and 2.5% compared with the EKF. The data curve can better fit the original data curve. The smoothness value has dropped by 43.9%, 11.4%, 49.4%, and the smoothness of the curve has been greatly improved. Therefore, the TWEKF proposed has stronger noise reduction ability in processing data. The research results provide a certain reference for the further development of more powerful data processing algorithms.

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