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Evaluating Measurement Quality in Kalman Filtering Using Second-Order Mutual Differences of Redundant Measurements

Yuze Wu¹ | Dekai Jiang² | Liuyang Jiang^{1*}

¹School of Information and Control Engineering, Qingdao University of Technology, Qingdao, 266555, China

²School of Automation, North China Electric Power University, Baoding 071003, China

Correspondence

Liuyang Jiang, School of Information and Control Engineering, Qingdao University of Technology, Qingdao 266555, China
Email: jiangliuyang@qut.edu.cn

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Abstract

With advancements in technology, accurate signal detection and state parameter estimation have become increasingly critical across diverse fields, including radar, sonar, communications, video image processing, and fault diagnosis. Sensor data acquisition is fundamental to digital signal processing systems; however, sensor measurements inherently contain noise, which cannot be entirely eliminated but only minimized. Kalman filtering is widely recognized as an effective method for noise reduction and state estimation. Nevertheless, the presence of outliers can adversely affect the adaptive Kalman filter's estimation accuracy, particularly regarding noise covariance and state parameters. This paper introduces a second-order mutual difference (SOMD) algorithm utilizing redundant measurements to evaluate measurement quality and mitigate the influence of abnormal observations. The effectiveness of the proposed algorithm is validated through numerical simulations and motion model simulations.

KEYWORDS

Adaptive Kalman filtering, Second-order mutual difference, Abnormal measurement, Evaluating Measurement Quality

1 | INTRODUCTION

The Beidou Satellite Navigation System (BDS) is a global satellite navigation system independently developed and operated by China. BDS has the characteristics of independence, openness, compatibility, advanced technology, stability and reliability, promoting the formation of the satellite navigation industry chain, a complete national satellite navigation system, and the advantage of two-way communication. It also has strong encryption measures, high security, reliability and stability, and is suitable for application in important fields and departments[1]. Kalman filtering (KF) is a commonly used information fusion filtering algorithm in integrated navigation system. However, due to the need for precise model construction in KF, it can lead to poor results such as signal divergence and distortion after Kalman filtering. This makes it difficult to achieve the desired filtering effect under complex nonlinear conditions in practice. Therefore, many scholars have proposed improved algorithms that have achieved good results on this basis, such as Extended Kalman Filter (EKF) algorithm[2], Unscented Kalman Filter

(UKF) algorithm[3], Cubature Kalman Filter (CKF) algorithm[4], Particle Filter (PF) algorithm[5]. Even filtering algorithms that combine neural networks with Kalman filtering to improve the filtering accuracy of integrated navigation technology[6]. However, these Kalman filtering algorithms have certain limitations in handling measurement errors. Measurement data is often affected by various noises and interferences, which may lead to the insensitivity of Kalman filters to measurement data errors, thereby reducing the accuracy of estimation results[7].

In practice, abnormal measurement values often arise from factors like equipment errors, environmental changes, and interference, significantly impacting data analysis and system accuracy. Thus, managing these anomalies is crucial for reliable data analysis. Observation quality assessment evaluates the observation data's quality within a system, aiming to identify and mitigate various errors and noise. This process ensures data reliability, enhancing system predictions, estimations, and control. This assessment targets identifying and removing outliers due to measurement errors, instrument malfunctions, anomalies, system bottlenecks, and data loss, thereby improving data accuracy and reliability. Addressing abnormal measurements is essential, as they can skew data analysis and lead to false conclusions. By eliminating these values, we can extract more accurate information, boosting experiment and system efficiency[8]. Hence, assessing observation quality and managing anomalies are vital for precise measurements and effective data analysis.

As an extension of traditional Kalman filtering, scholars have proposed IAE and RAE algorithms, and even Robust adaptive Kalman filter (RAKF). These algorithms have many advantages. However, all the algorithms described above are based on the information provided by the innovation or the residual. Therefore, state estimation errors can directly disrupt the estimation of noise covariance or state error covariance matrix, leading to inaccurate or even divergent output of the filter[9]. To mitigate these limitations, researchers have developed an enhanced algorithm that can adaptively estimate the measurement noise covariance matrix (R) using the second-order mutual-difference (SOMD) sequences derived from redundant measurements[10]-[11]. The core concept involves generating the first-order self-difference sequence and the SOMD sequence for two distinct measurement systems, leveraging the variation relationship of the measurement sequence when the observed object is monitored by two different measurement systems. This approach facilitates the derivation of the observation system's noise statistical characteristics through statistical methods. However, this algorithm's applicability to most practical systems is limited due to its reliance on redundant measurements, often rendering its cost unsatisfactory. Subsequently, an alternative approach, the redundant measurement-based adaptive Kalman filtering (RMAKF) algorithm, was introduced. This algorithm, by establishing a pseudo-measurement, enables the estimation of the measurement noise covariance matrix (R) in systems with a single measurement, utilizing the SOMD algorithm[12]-[13].

Although the SOMD algorithm based on redundant measurements can address the issue of decoupling the measurement noise covariance estimation from the state estimation error in adaptive Kalman filter (i.e., the adaptive estimation of measurement noise covariance is unaffected by state estimation errors), the presence of outliers in the measurement system can significantly impact adaptive Kalman filtering, leading to deteriorated filtering performance and even causing the results to diverge.

This paper utilizes the advantages of the SOMD technique to evaluate observation quality and suppress anomalies in it. Initially, a comprehensive overview of the principles underpinning Kalman filtering and the SOMD algorithm is presented. Subsequently, leveraging the distinctive features of the SOMD algorithm, a methodology for evaluating the quality of measurement data has been developed. Through the statistical analysis of these evaluation results and the employment of threshold determination strategies, this method enables the identification and suppression of aberrant measurements within the observed data.

2 | RELATED WORKS

2.1 | Overview of Standard Kalman Filter

Kalman Filter is an efficient recursive filter that can estimate the state of a dynamic system from a series of measurements containing noise by minimizing the variance of estimation errors. It is very powerful in multiple aspects: it supports estimation of past, present, and future states, even when the accurate characteristics of the modeling system are unknown.[14]

For a linear discrete-time system as follows:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (1)$$

$$z_k = Hx_k + v_k \quad (2)$$

where x_k is the state variable, A is the state transition matrix, B is the control matrix, u_k is the control input, Z_k is the observation vector, H is the measurement matrix, w_k is the process noise, v_k is the measurement noise, the noise is unmeasurable and is a manifestation of uncertainty. It is generally considered to follow a normal distribution $P(w) \sim (0, Q)$, $P(v) \sim (0, R)$, with an expected value of 0, Q and R are the covariance matrix. W and V are independent of each other, $cov[w_k, v_k] = 0$.

The operational framework of Kalman filtering is divided into two steps: the Time Update and the Measurement Update, which are also commonly referred to as the Prediction and Correction steps in the literature.

The first step is to predict, where we obtain a prior estimate:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \quad (3)$$

Then calculate the covariance matrix of the prior error

$$P_k^- = AP_{k-1}A^T + Q \quad (4)$$

The second step is Correction. First, calculate the Kalman gain

$$K_k = \frac{P_k^- H^T}{HP_k^- H^T + R} \quad (5)$$

Then calculate the posterior estimate

$$\hat{x}_k = \hat{x}_k^- + K_k (Z_k - H\hat{x}_k^-) \quad (6)$$

This is also our goal, Obtained $\hat{x}_k$ is the optimal estimate value, Finally, in preparation for the next round, the error covariance matrix needs to be updated as

$$P_k = (I - K_k H) P_k^- \quad (7)$$

It can be seen that each calculation will use the previous result, and at the beginning, it needs to be assigned an initial value $\hat{x}_0$ and P_0 .

The derivation and proof of formula (3) (7) can be found in reference 4, and will not be elaborated in this article.

For the sake of intuitiveness, we provide a process diagram of the Kalman filter, as shown in Figure 1.

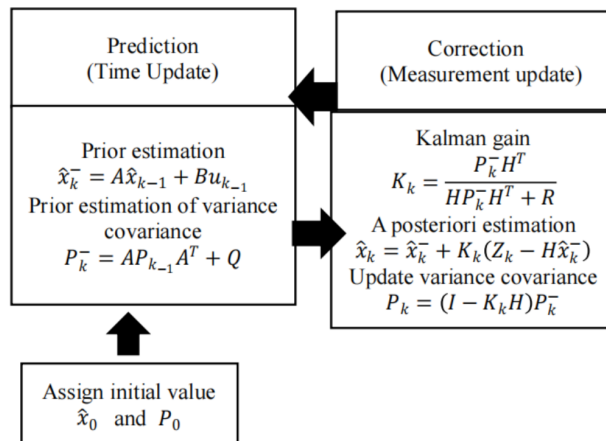


FIGURE 1 Schematic diagram of Kalman filter calculation

2.2 | Overview of SOMD algorithm

An estimation theorem for measurement noise covariance with range constraints based on redundant measurements as follows:

Theorem 1: Assuming Z_k^1 and Z_k^2 are the measurement values of two different observation systems on the measured object at time k , which are redundant measurements of each other. It is defined as [10].

$$z_k^i = z_k^r + s_k^i + v_k^i \quad (8)$$

In the formula, z_k^r is the ideal observation value of Z_k ; s_k^i is the deterministic error of the observation system, v_k^1 and v_k^2 is the independent measurement white noise at time k , respectively R_k^1 and R_k^2 .

Construct the first-order self-difference sequence and SOMD sequence of two measurement systems as follows:

$$\Delta Z_k^i = z_k^i - z_{k-1}^i, \quad i = 1, 2 \quad (9)$$

$$\Delta(\Delta Z_k^{12}) = \Delta Z_k^1 - \Delta Z_k^2 \quad (10)$$

If there is a level difference in accuracy between two measurement systems

$$E[V_k^2 (V_k^1)^T] \ll E[V_k^1 (V_k^1)^T] \quad (11)$$

So the variance of noise with larger variance can be approximated as:

$$\hat{R}_k^1 \approx \text{Var}[\Delta(\Delta Z_k^{12})]/2 \quad (12)$$

However, the need to satisfy the range condition limits the application of Theorem 1. The following introduces a method for estimating the variance of observation noise in a redundant measurement system, where there is no order of magnitude difference between the noises.

The measurement noise variance estimation theorem based on redundant measurement noise with no range constraint as follows:

Theorem 2: Having the same assumption as Theorem 1, there is no need to satisfy the level difference condition of Formula (11), When the accuracy of two measurement systems is equivalent, that is, there is no need to meet the level difference condition, the observation noise variance matrix R_k^1 and R_k^2 the approximate estimate is:[11]

$$\hat{R}_k^1 = \text{Var}(v_k^1) = \{\text{Var}[\Delta(\Delta Z_k^{12})] + [\text{Var}(\Delta Z_k^1) - \text{Var}(\Delta Z_k^2)]\}/4 \quad (13)$$

$$\hat{R}_k^2 = \text{Var}(v_k^2) = \{\text{Var}[\Delta(\Delta Z_k^{12})] - [\text{Var}(\Delta Z_k^1) - \text{Var}(\Delta Z_k^2)]\}/4 \quad (14)$$

In the formula, $\text{Var}(\Delta Z_k^1)$ and $\text{Var}(\Delta Z_k^2)$ respectively represents the variance of the first-order difference sequences of two measurement systems; $\text{Var}[\Delta(\Delta Z_k^{12})]$ represents the variance of the SOMD sequences of two measurement systems.

Theorem 2 breaks away from the constraint in theorem 1 that the noise values between redundant measurements must satisfy the condition of level differences, offering a broader range of applications.

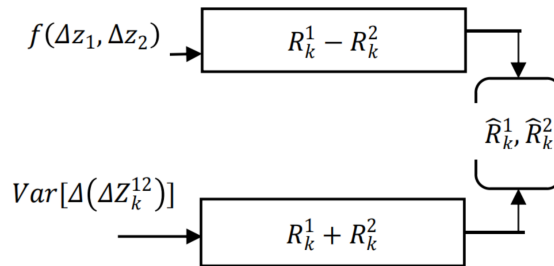


FIGURE 2 Calculation diagram of Theorem 2

The design concept of the measurement noise variance estimation theorem based on redundant measurement noise without level difference constraint is shown in Figure 2.

Theorem 2 utilizes continuous difference operation to obtain the SOMD sequence of the measurement system, eliminating the measurement of the true value Z and the change in true value ΔZ and the relationship between the statistical characteristics of first-order differential sequences and the measurement noise variance, two equations were constructed for the correlation between the noise variance of measurement systems and the autocorrelation of measurement value differential sequences. Under the condition of unconstrained noise variance for redundant measurement systems, accurate estimates of noise variance for each system can be made separately. This article evaluates the observation quality and suppresses abnormal measurements based on Theorem 2.

3 | DETECTION AND SUPPRESSION OF MEASUREMENT QUALITY USING THE SOMD ALGORITHM

As is widely acknowledged, a multitude of factors can lead to anomalies in measurements. Therefore, the presence of outlier values can significantly impact the adaptive Kalman filter's estimation of noise covariance and the results of state estimation. In response to this issue, this section will introduce a method for detecting and mitigating abnormal measurement values. This method aims to enhance the reliability and accuracy of the measurement data, ensuring that the impact of these anomalies on the adaptive estimation of noise covariance and the results of state estimation is minimized.

3.1 | Judgment of abnormal measurements

Suppose $z_2(k)$ is an abnormal observation value, it contains a significant measurement error:

$$z_k^2 = z_k^r + s_k^2 + v_k^2 + Err_k \quad (15)$$

where z_k^r is the ideal observation value of Z_k , s_k^2 is the deterministic error of the observation system; v_k^2 is the noise, Err_k is the abnormal errors. In the process of calculating second-order mutual differences, Err_k unable to be offset and retained within ΔZ_k^{12} :

$$\Delta Z_k^{12} = [v_k^2 - v_{k-1}^2] - [v_k^1 - v_{k-1}^1] + Err_k \quad (16)$$

Due to the significantly larger amplitude of the abnormal error compared to the noise term, namely:

$$|Err_k| \gg |[v_k^2 - v_{k-1}^2] - [v_k^1 - v_{k-1}^1]| \quad (17)$$

So,

$$|\Delta Z_k^{12}| \gg |[v_k^2 - v_{k-1}^2] - [v_k^1 - v_{k-1}^1]| \quad (18)$$

Therefore, it can be used $\kappa\sigma$ Guidelines for Identify ΔZ_k^{12} , When ΔZ_k^{12} satisfies the following equation, it is considered to have abnormal measurements:

$$|\Delta Z_k^{12}| > \kappa \sqrt{\Delta[\Delta Z_k^{12}]} \quad (19)$$

In the formula κ Is the proportional coefficient. Simultaneously considering the stationarity of noise statistical characteristics, there are:

$$|\Delta Z_k^{12}| > \kappa \sqrt{\Delta[\Delta Z_{k-1}^{12}]} \quad (20)$$

According to equation (3.1.9), this criterion is further transformed into:

$$|\Delta Z_k^{12}| > \kappa \sqrt{2[\hat{R}_{k-1}^1 + \hat{R}_{k-1}^2]} \quad (21)$$

where $\hat{R}_{k-1}^1, \hat{R}_{k-1}^2$ are the estimated measurement noise values of the two measurement systems calculated through the above theorem can be considered as 3 in practical applications. If there is an outlier point ΔZ_k^{12} in the second-order cross difference sequence, then when using statistical sampling to execute the above theorem algorithm, ΔZ_k^{12} and its corresponding self differences ΔZ_k^1 and ΔZ_k^2 should not participate in the calculation.

When anomalies are detected in the measurement of the filtering system, the measurement noise covariance matrix (R), can be dilated to prevent the resulting decrease in filtering accuracy.

3.2 | Adaptive dilation of R

Based on the anomaly measurement detection problem proposed in section 3.1, the method of adaptive dilating R can be used to solve it. When Equation (21) is satisfied, we consider the measurement result to be abnormal, and the estimated value should be significantly different from the measured value, placing greater trust in the predicted value. To distance the Kalman filter's estimated value from the measured value, we can increase R. The larger R is, the less correlation there is between the estimated and measured values. Therefore, in the event of abnormal measurements, R should be adaptively expanded as:

$$\bar{R} = \beta \hat{R} (\beta > 1) \quad (22)$$

This ensures that the Kalman filter measurements are more accurate.

4 | SIMULATIONS

Two numerical simulation cases are conducted to rigorously evaluate the robustness of the proposed algorithm: the first case examines signal processing performance through empirical data analysis, while the second case investigates system dynamics using kinematic model implementation.

4.1 | Signal simulation

In the simulation, let Z represent the true angular velocity being measured (in units of °/s), and its variation with respect to time can be expressed as.

$$Z(t) = \sin(2t) + \cos(t) + \log(0.5 + t/2) + 10 \quad (23)$$

The measurement equation for the redundant measurement process is given by.

$$Z_i = Z + b_i + n_i (i = 1, \dots, N) \quad (24)$$

In the given equation, b_i and n_i represent the zero bias and the measurement noise of the i-th measurement process, respectively, with the assumption that b_i is a constant.

The simulation experiment was conducted over a duration of 50 seconds, with a measurement frequency set at 100 Hz. The measurement bias was set to zero, and the noise variances of Sensor 1 and Sensor 2 were set to 1 and 2, respectively. The performance of the SOMD method with and without outlier detection, as well as the random weight method, was compared based on the variation in noise variance over time during the Z(t) measurement process under the presence of outliers. The true angular velocity values and the measurements from both sensors are depicted in Figure 3, which illustrates the occurrence of some outliers at certain times. The curves representing the variation in the noise variance over time, as estimated by the SOMD method and the random weight method, are shown in Figures 4 and 5, respectively. In Figure 4, the SOMD algorithm incorporates outlier detection, while in Figure 5, the algorithm does not. From these figures, it is evident that the noise variance estimated by the SOMD method converges more rapidly to the true value compared to the random weight method. Moreover, when outlier detection is employed, the estimated noise variance remains closer to the true value even during instances of abnormal measurements from the sensor.

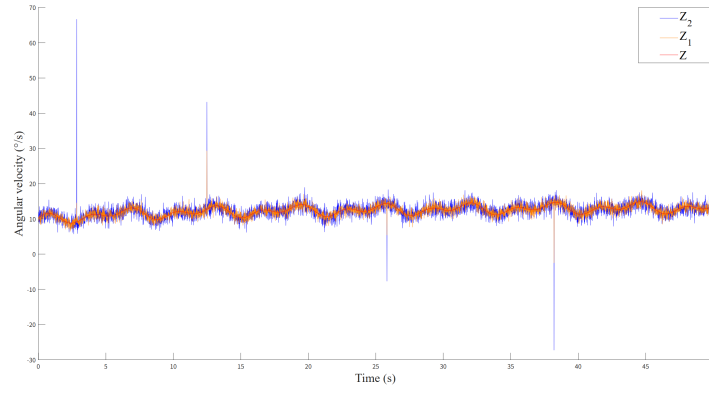


FIGURE 3 True measured signal Z and measurement processes Z_1 and Z_2

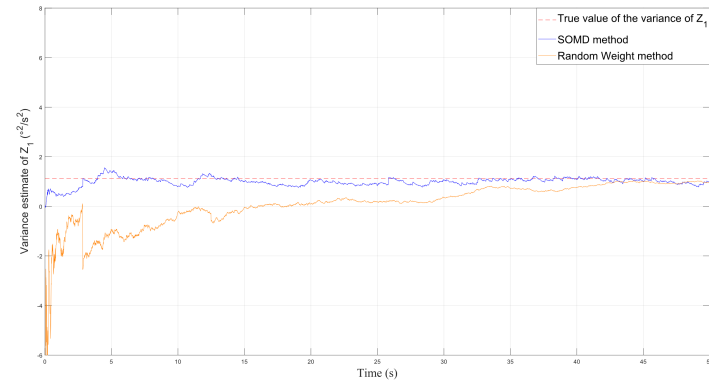


FIGURE 4 Z_1 measurement noise variance estimation result (including outlier detection)

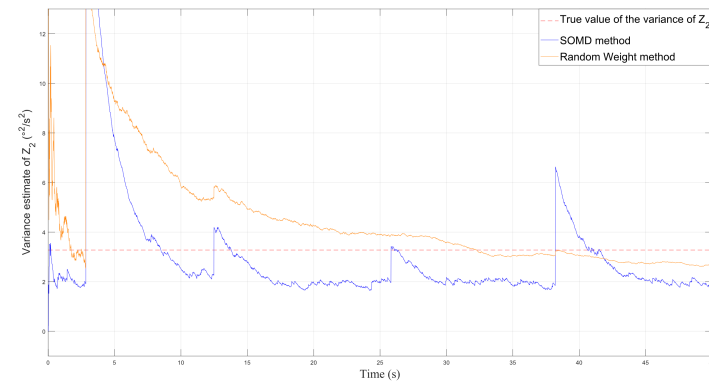


FIGURE 5 Z_2 measurement noise variance estimation result (excluding outlier detection)

4.2 | Motion simulation

A small car moves along a straight line at a constant speed, and the measurements in the system are redundant, making x_1 represents the vehicle position measured by 1, $\dot{x}_1$ represents the vehicle speed measured by 1, making x_2 represents the vehicle position measured by 2, $\dot{x}_2$ represents the vehicle speed measured by 2. Assuming that measurement 1 observes the position with measurement noise $v_1(t)$, Assuming that measurement 2 observes the position with measurement noise $v_2(t)$. Due to the vehicle

moving at a constant speed in a straight line, $\ddot{x}(t) = 0$.

The system status can be described as $\dot{x}(t) = [x(t), \dot{x}(t)]$, then the discrete system equivalent to the state equation and output equation of the system can be expressed as:

$$x_k = Ax_k + w_k \quad (25)$$

$$z_{1k} = Hx_k + v_{1k} \quad (26)$$

$$z_{2k} = Hx_k + v_{2k} \quad (27)$$

In the above equation:

$$A = \begin{bmatrix} 1 & \Delta T \\ 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad (28)$$

Assuming the mean and covariance of the initial position are:

$$\hat{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, P_1 = \begin{bmatrix} 0.25 & 0 \\ 0 & 0.25 \end{bmatrix} \quad (29)$$

$$\hat{x}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, P_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (30)$$

Meanwhile, assuming that the covariance between process noise and observation noise is:

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R_1 = 0.5, R_2 = 1 \quad (31)$$

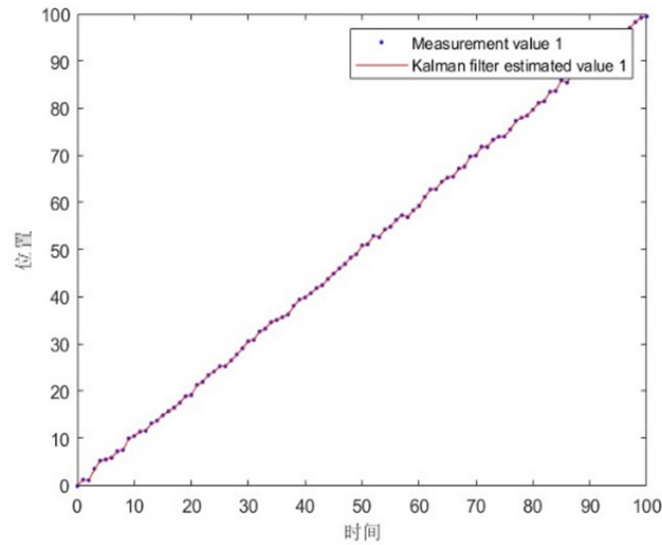


FIGURE 6 Schematic diagram of measurement 1 and Kalman filter estimation value

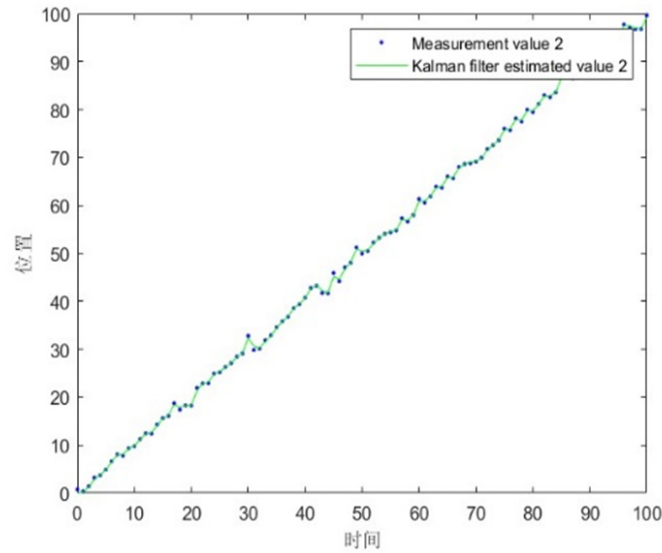


FIGURE 7 Schematic diagram of measurement 1 and Kalman filter estimation value

Figure 6 and Figure 7 show the results of running Kalman filtering when $\Delta T = 1$. It can be seen that the Kalman filter values in measurement system 1 are more closely related to the measured values, precisely because the measurement error in measurement system 1 is smaller and the observation values are more trusted.

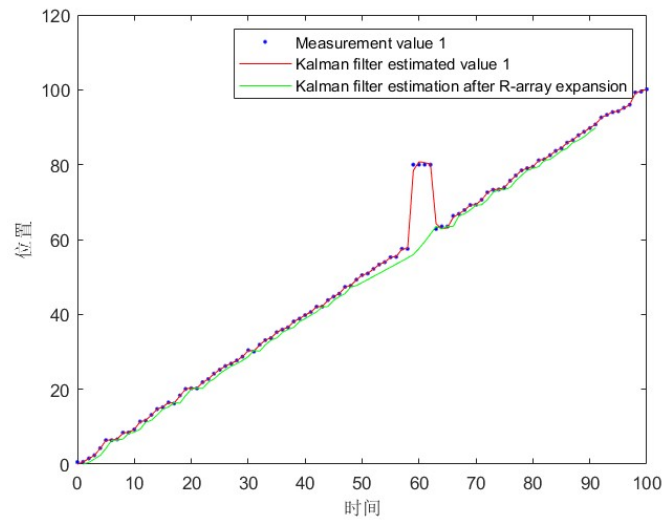


FIGURE 8 Filtering after expanding the R matrix with abnormal measurements

From Figure 8, it can be seen that near the abnormal measurement values, the original standard Kalman filter value (red line) still fits the measurement value, but at this point it is far from the actual value. However, after the expansion of the R-array, the filter value (green line) is far away from these abnormal measurement values, and the estimated value of the filter is close to the actual value. Implement suppression of abnormal measurements.

5 | CONCLUSION

This article has introduced the basic principles of standard Kalman filters and the SOMD algorithm for estimating noise covariance. The abnormal values have been detected by the SOMD algorithm can be effectively eliminated, thereby improving the quality of observation data. By conducting a thorough investigation in this study, we aim to offer valuable insights for enhancing the performance of Kalman filtering. Simultaneously, we strive to introduce a novel method for researchers in related disciplines.

The SOMD algorithm for estimating noise covariance needs to satisfy redundant measurement conditions, which are difficult to achieve in many practical problems, whether based on measurement conditions or measurement costs. Therefore, in order to make the SOMD algorithm more widely applicable, it should be considered to extend it to situations with a single measurement system. It can be assumed that a reasonable and effective pseudo measurement can be constructed as a redundant measurement to achieve effective estimation of the observation noise variance of a single measurement system. The SOMD noise covariance estimation algorithm based on redundant measurements will have a wider range of applications. This will be the focus of our next steps.

AUTHOR CONTRIBUTIONS

Conceptualization, Liuyang Jiang; **Methodology**, Liuyang Jiang; **Software**, Yuze Wu; **Validation**, Yuze Wu; **Formal analysis**, Dekai Jiang; **Investigation**, Dekai Jiang; **Resources**, Liuyang Jiang; **Data curation**, Dekai Jiang; **Writing - original draft**, Yuze Wu; **Writing - review & editing**, Yuze Wu; **Visualization**, Yuze Wu; **Supervision**, Liuyang Jiang; **Project administration**, Liuyang Jiang. All authors have read and agreed to the published version of the manuscript.

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Yuze Wu has been pursuing a Bachelor's degree in Building Electrical and Intelligenzation at Qingdao University of Technology since September 2023. He is interested in the field of control and is currently researching Kalman filtering. In 2024, he won the first prize in the Control category at the Shandong Provincial Competition of the National Undergraduate Electronic Design Contest.



Dekai Jiang received his B.Eng. degree in Building Electricity and Intelligence from Qingdao University of Technology, Qingdao, China, in 2023, and since September 2024, he has been pursuing her M.s. degree in Control Engineering from North China Electric Power University, Baoding, China. His research interests include machine learning.



Liuyang Jiang received her B.S. degree in Measurement Control Technology and Instruments from Qingdao University of Technology, Qingdao, China, in 2008, and her M.S. degree in Control Theory and Control Engineering from Shandong University of Science and Technology, Qingdao, China, in 2012, and her Ph.D. degree in Control Theory and Control Engineering from Beihang University, Beijing, China, in 2020. Since 2021, she has been a Lecturer in School of Information and Control Engineering, Qingdao University of Technology. Her research interests include adaptive Kalman filtering, state estimation, and stochastic systems.