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A multi-sensor data fusion algorithm based on consistency preprocessing and adaptive weighting

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ABSTRACT
In the data collection of a multi-sensor system, there are problems with large errors, conflicts, and redundancy. To solve the above problem, a multi-sensor data fusion algorithm based on anomaly data preprocessing and adaptive weighted estimation is proposed. To improve the reliability of the algorithm, first, for a single sensor measurement signal sequence, a consistency preprocessing using the off-centre distance method is performed, and the weighting factor of each measurement data is calculated. Then, the measurement signal sequence is weighted and fused; Secondly, in response to the uneven distribution of measurement errors among multiple sensors in different directions, an adaptive weighted data fusion method based on the principle of optimal weight allocation is proposed. The proposed method was compared with the adaptive weighting method and arithmetic mean method. The simulation results showed that the total mean square error of the data fusion results obtained using the proposed algorithm is smaller. The proposed algorithm can effectively improve the accuracy of data measurement, reduce redundancy, and improve the stability of data measurement.

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I. Introduction

Multi-sensor data fusion is a new technology developed in recent years [1]. It is characterized by using multiple sensors to measure the same measurement object, to obtain the multi-source information of the object. It makes full use of the redundancy and complementarity of multi-source information, and fuses this information, compared with a single sensor, it can form a high-quality and reliable judgment of the surrounding environment reality [2]. Even if the environment changes and some equipment of the system suffers from technical failure or damage, the quality of such judgment can be maintained.

Wireless Sensor Network (WSN) is composed of a large number of sensor nodes with sensing, computing, and wireless communication capabilities. It has the characteristics of small node size, low cost, multi-hop ad hoc network, and large sensing area. WSN has a wide range of applications such as environmental monitoring [3], habitat monitoring [4], military applications [5], weather monitoring [6], smart grid [7], traffic monitoring [8], and forest fire detection [9], etc. In WSN, a plethora of small-sized application-specific sensor nodes are randomly deployed in the sensor field. These sensor nodes collect information and forward it to their managing node (sink node or cluster head (CH)) via wireless communication. The nodes are resource-constrained in terms of energy, computational capability, storage capacity, and communication range [10]. WSN generates a large amount of redundant data while monitoring information. On the one hand, processing and transmitting redundant data wastes limited energy and network bandwidth; On the other hand, interference factors and sensor measurement accuracy lead to errors in system monitoring results, and the random occurrence of faulty nodes also reduces the reliability of the system to a certain extent. How to reduce redundant data, reduce node energy consumption, improve network reliability, and extend its effective lifetime has become a very important issue in WSN research [11].

Heterogeneous multi-sensors play an important role in information perception, the acquired data may contain some ambiguous and conflicting information due to the limitations of multi-sensor devices' measurement accuracy and the complexity of the working environment, which may result in inaccurate data-fusion decisions [12]. Consequently, the way to better handle multi-sensor data and improve data-fusion accuracy is a popular research direction in the field of data-fusion technology [13]. One of the effective ways to improve data reliability, and accuracy, and reduce redundancy is to preprocess multi-source sensor data and implement effective data fusion mechanisms, correct data with

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large deviations, delete unreliable data, and remove redundant and highly repetitive related data. Common data-fusion algorithms currently include Kalman filtering [14], Bayesian estimation [15], Dempster–Shafer (D-S) evidence theory [16], and artificial neural networks [17], etc. Bayesian networks and D-S evidence theory are commonly used to deal with the uncertainty in multi-sensor data, which frequently results in anomalous data. Statistical algorithms represented by Bayesian theory need to obtain prior knowledge and probability distribution before fusing multi-sensor data to calculate the reliability of sensors [18]. Artificial intelligence algorithms represented by artificial neural networks (ANNs), can handle the problems of unclear and uncertain nonlinear systems. However, complex structures and random parameters can lead to unstable fusion results [19]. The fusion algorithm based on the support function is a typical information-theoretic algorithm, which can obtain the relationships between data and avoid the adverse effects of untrusted data on the fusion results [20]. Alessandra De Paola [21] proposes a context-aware, self-optimizing, and adaptive system based on a three-layer architecture. The lowest level sensors collect heterogeneous data, while the middle level utilizes dynamic Bayesian principles to handle measurement data inaccuracies and infer estimates based on contextual information. The highest level achieves a free optimization process by collecting sensor set data to improve the accuracy of monitoring values. Sergey V. Muravyov [22] proposed a method of interval voting based on preference aggregation form. Allowing inaccurate measurement data from adjacent multiple sensors within narrow uncertainty boundaries to determine the correction values of measurement parameters, achieving good measurement accuracy. To optimize the errors, and useless, and redundant data in various sensor network models, a fuzzy inference system is introduced for data fusion to improve accuracy and fusion quality [23]. Shahaboddin Shamshirband [24] adopts the support vector regression machine method to fuse the data of various sensor arrays to improve the accuracy of the data. In the attitude measurement process of guided drilling systems, to eliminate the interference of vibration and quickly obtain accurate attitude parameters of guided drilling tools, a new method of multi-sensor dynamic attitude combination measurement is proposed [25].

In practical measurement, because there is a noise in the measurement data, the estimated value obtained from the measurement data also has an estimation error, which is also a random quantity. Therefore, the mean square error is generally used as an index to evaluate the quality of an estimation measurement algorithm. When using a single sensor, to reduce the mean square error of the estimation value, it is necessary to increase the sample length of the measurement data, and the increase in the sample length of the measurement data will lead to increased computation and reduced convergence speed, which will reduce the real-time performance of the measurement. To solve this problem, many researchers have applied multi-sensor data fusion technology to the research of estimation algorithms. Guiling Sun [26] proposed a multi-sensor data fusion method based on trust degree to quantify the trust degree between two sensor data and measure the comprehensive trust degree of each sensor data. Donghui Li [27] proposed an adaptive weighted estimation algorithm for multi-sensors, which is used to estimate a non-random quantity from measurement data containing observation noise. Pei Shi [28] proposed a data fusion method using a novel function that is Dynamic Time Warping time-series strategy improved support degree for enhancing data quality.

Based on the adaptive weighting method and considering the measurement bias caused by environmental factors, in this paper, a multi-sensor data fusion algorithm that combines consistency preprocessing and adaptive weighting is proposed to fuse multiple sets of measurement signal sequences. Firstly, the off-centre distance method is used to preprocess the consistency of the measurement signal sequence of a single sensor, and then the weighting factor of each measurement data is calculated and weighted for fusion. Afterwards, based on single-sensor data fusion, adaptive weighted estimation is performed on multiple sets of measurement signal sequences from multiple sensors to obtain more accurate measurement results. In the experimental section, the proposed method was compared with the adaptive weighting method and arithmetic mean method, and the total mean square error was used to evaluate the fusion performance of different methods. The rest of this article is organized as follows. The second section proposes a multi-sensor data fusion method based on consistency preprocessing by using off-centre distance and adaptive weighted estimation. The third section designed an experimental plan and analyzed the experimental results. Finally, the fourth section provides a summary of this article.

II. Multi-sensor data fusion algorithm based on consistency preprocessing and adaptive weighting

In this paper a two-level fusion structure model of multi-sensor data based on consistency preprocessing and adaptive weighting was proposed to improve measurement accuracy, which is shown in Figure 1. Firstly, the consistency test theory based on the off-centre distance is used to preprocess the measured data of each sensor. The measured data with great deviation due to the failure of some sensors or the influence of environmental factors in the multi-sensor system are eliminated. The off-centre distance method is used to calculate the weighting factor, and the measured values of

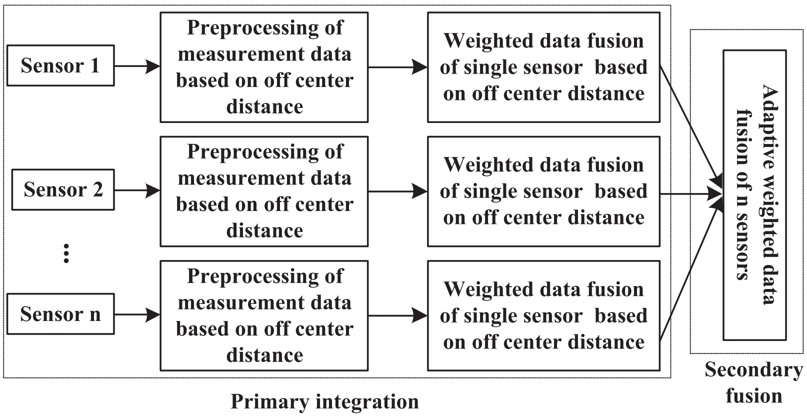

Figure 1. The two-level fusion structure model of multi-sensor data based on consistency preprocessing and adaptive weighting.

each sensor at different times are fused with the previous historical measured values for estimation, then the first level fusion result for single sensor measurement data is obtained. The second level of fusion is based on the adaptive weighting method adopted by all sensors in the space. In the sense of minimum total mean square error, the optimal weighting factor corresponding to all sensors is adaptively found, so that the total mean square error of the fusion estimation results at this time reaches the minimum value, and the final fusion estimation value is output.

A. Single sensor data fusion

When using a multi-sensor system to measure data, when some sensors in the system have a fault or are affected by environmental factors, the measurement data has a large deviation. If all measurement data are directly fused without timely inspection and elimination of data exceeding a certain limit, the final data fusion accuracy will be affected and the mean square error of the fusion system will be increased. Therefore, the off-centre distance method is used to preprocess and fuse the measured data of a single sensor.

Suppose that a multi-sensor system is composed of m sensors of the same kind, in which the kth sensor has n observations, being respectively. Let the average of these n observations be $\bar{x}$, and use the average as the centre value. Let $d_i = \left|x_i - \bar{x}\right|$, then it can indicate the distance of observation value xi from the centre value $\bar{x}$. If d_i is larger, it indicates that the deviation caused by observation value x_i is larger. On the contrary, it indicates that the smaller the deviation caused by the observation value xi is. Therefore, the off-centre distance of a single sensor observation can be defined as follows:

Definition 1 Let the n observed values of the kth sensor be $x_1, x_2, \ldots, x_n$ respectively, their average value is $\bar{x}$, and the distance d_i of observation value xi from the centre value $\bar{x}$ can be expressed as: $d_i = \left|x_i - \bar{x}\right|$ (i = 1,2,… ,n)

When the deviation distance of an observation value is greater than a certain degree, it will affect the final data fusion accuracy. It can be considered to eliminate it, which is the significance of the consistency test.

According to the method described above, the n observations $x_1, x_2, \ldots, x_n$ of the kth sensor are preprocessed for consistency, and c observations are eliminated in the order of the deviation from the centre from the largest to the smallest. After that, the remaining n–c observations that have been preprocessed for consistency are weighted for fusion estimation. The smaller the deviation from the centre, the higher the consistency with other observations, and the larger the corresponding weighting factor should be. According to the guidance of this idea, the weighting factor $w(i)$ of the ith observation can be calculated as follows:

$$w(i) = \frac{1}{[d(i)+1]\sum_{i=1}^{n-c}\frac{1}{[d(i)+1]}} \tag{1}$$

Where $0 \le w(i) \le 1$, and $\sum_{i=1}^{n-c} w(i) = 1$ was met. To avoid the complexity of calculating the weighting factor when the off- centre distance is 0, the method $d(i) + 1$ was adopted here. The weighted fusion estimate of the remaining n–c observations after preprocessing of the kth sensor can be expressed as:

$$\hat{x}_k = \sum_{i=1}^{n-c} w(i)x_i{}' \tag{2}$$

$\hat{x}_k$ is the first level fusion estimate for the kth sensor when the measurement data sample length is n. Similarly, the first level fusion estimate can be obtained for the other m-1 sensors when the measurement data sample length is n.

B. Multi-sensor data fusion

The second level of fusion is the optimal fusion estimation based on spatial multi-sensor. The adaptive weighted fusion estimation algorithm is adopted. Under the condition of minimum total mean square error, the optimal weighting factor is found adaptively according to the estimated values obtained by different sensors at the same time after the first level of fusion, so that the fusion estimated values of the measured parameters at that time reach the optimal.

Suppose that the observed values of m sensors are $X_1, X_2, \ldots, X_m$ respectively, they are independent of each other, and are unbiased estimates of the true value X, the corresponding variances of the observed values of each sensor are ${\sigma_1}^2, {\sigma_2}^2, \ldots, {\sigma_m}^2$ respectively, and the weighting factors of each sensor are $W_1, W_2, \ldots, W_m$ respectively, then the fused estimated values and weighting factors meet the following equation:

$$\hat{X} = \sum_{k=1}^{m} W_k X_k, \ \sum_{k=1}^{m} W_k = 1 \tag{3}$$

The total mean square error σ^2 of the multi-sensor data after fused is as follows:

$$\begin{aligned}\sigma^2 &= E\left[\left(X - \hat{X}\right)^2\right] \\ &= E\left[\left(X - \sum_{k=1}^{m} W_k X_k\right)^2\right] \\ &= E\left[\sum_{k=1}^{m} {W_k}^2 (X - X_k)^2 \right. \\ &\quad \left. + 2 \sum_{i=1, j=1, i \neq j}^{m} W_i W_j (X - X_i)(X - X_j)\right]\end{aligned} \tag{4}$$

Since $X_1, X_2, \ldots, X_m$ are independent of each other and unbiased estimates of the true value X, there is $E[(X - X_i)(X - X_j)] = 0$ (where $i = 1, \ldots, m, j = 1, \ldots, m$, and $i \neq j$), and σ^2 can be expressed as:

$$\begin{aligned}\sigma^2 &= E\left[\sum_{k=1}^{m} {W_k}^2 (X - X_k)^2\right] \\ &= \sum_{k=1}^{m} {W_k}^2 E[(X - X_k)^2] = \sum_{k=1}^{m} {W_k}^2 {\sigma_k}^2\end{aligned} \tag{5}$$

It can be seen from (5) that the total mean square error σ^2 is a multivariate quadratic function of each weighting factor, so there must be a minimum value. The minimum value is obtained from the extreme value of a multivariate function whose weighting factor satisfies the constraint condition of (3). Using the Lagrangian multiplier method to solve the extreme value of this condition, the weighting factor corresponding to the minimum total mean square error can be obtained as:

$$W_k{}^* = 1 \Bigg/ \left({\sigma_k}^2 \sum_{i=1}^{m} \frac{1}{{\sigma_i}^2}\right) \quad k = 1, 2, \ldots, m \tag{6}$$

At this time, the corresponding minimum value of the total mean square error is:

$$\sigma_{\min}{}^2 = 1 \Bigg/ \left(\sum_{k=1}^{m} \frac{1}{{\sigma_k}^2}\right) \tag{7}$$

The above estimation is based on the measured value of each sensor at a certain time. When the true value X is constant, further fusion estimation can be made based on the first-level fusion estimate of each sensor's historical data.

Suppose $\hat{x}_k = \sum_{i=1}^{p} w(i) x_i'$, where $\hat{x}_k$ is the first level fusion estimate of the historical observation value of the kth sensor at a certain time, the second level fusion estimate at this time is $\tilde{X} = \sum_{k=1}^{m} W_k \hat{x}_k$, and the total mean square error of multi-sensor data at this time is:

$$\begin{aligned}\tilde{\sigma}^2 &= E\left[\left(X - \tilde{X}\right)^2\right] \\ &= E\left[\left(X - \sum_{k=1}^{m} W_k \hat{x}_k\right)^2\right] \\ &= E\left[\sum_{k=1}^{m} {W_k}^2 \left(X - \hat{x}_k\right)^2 \right. \\ &\quad \left. + 2 \sum_{i=1, j=1, i \neq j}^{m} W_i W_j \left(X - \hat{x}_i\right)\left(X - \hat{x}_j\right)\right]\end{aligned} \tag{8}$$

Since the observed value of each sensor is an unbiased estimate of the true value X, the first-level fusion estimates $\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_m$ must also be unbiased estimates of X, so $E\left[\left(X - \hat{x}_i\right)\left(X - \hat{x}_j\right)\right] = 0$, and the total mean square error is:

$$\begin{aligned}\tilde{\sigma}^2 &= E\left[\sum_{k=1}^{m} {W_k}^2 \left(X - \hat{x}_k\right)^2\right] \\ &= \sum_{k=1}^{m} {W_k}^2 E\left[\left(X - \hat{x}_k\right)^2\right] \\ &= \sum_{k=1}^{m} {W_k}^2 E\left[\left(X - \sum_{i=1}^{p} w(i) x_i'\right)^2\right]\end{aligned} \tag{9}$$

According to (4) and (5), $E\left[\left(X - \sum_{i=1}^{p} w(i) x_i'\right)^2\right] = \sum_{i=1}^{p} {w_i}^2 E[(X - {x_i}')^2] = \sum_{i=1}^{p} {w_i}^2 {\sigma_k}^2$, so $\tilde{\sigma}^2$ could be expressed as:

$$\tilde{\sigma}^2 = \sum_{k=1}^{m} W_k^2 \left(\sum_{i=1}^{p} w_i^2 \sigma_k^2\right) = \sum_{k=1}^{m}\sum_{i=1}^{p} W_k^2 (w_i^2 \sigma_k^2) \tag{10}$$

According to (5) and (6), the optimal weighting factor W_k^* corresponding to the minimum $\tilde{\sigma}^2$ is:

$$W_k^* = 1\Big/\left(\sigma_k^2 \sum_{i=1}^{m} \frac{1}{\sigma_i^2}\right) \tag{11}$$

At this time, the minimum value of the corresponding total mean square error is:

$$\tilde{\sigma}_{\min}^2 = \frac{\sum_{i=1}^{p} w_i^2}{\sum_{k=1}^{m} \frac{1}{\sigma_k^2}} = \sigma_{\min}^2 \sum_{i=1}^{p} w_i^2 \tag{12}$$

It can be seen from (12) that $\tilde{\sigma}_{\min}^2$ must be less than $\sigma_{\min}^2$. That is, the mean square error of multi-sensor data secondary fusion based on off-centre distance and adaptive weighting is less than the mean square error of adaptive weighting data fusion.

C. The proposed algorithm

The above theory is applied to the two-level fusion estimation of measurement data samples from m sensors. The calculation flow of the estimation algorithm is as follows:

① Calculate the off-centre distance $d(i)$ of n historical observations of the kth sensor at the sampling time t according to the definition, i = 1,2, … , n;

② Conduct consistency pre-processing for n historical observations of the kth sensor at the sampling time t, then remove c observation values in the order of large to small deviation from the centre;

③ For the historical observation value of the kth sensor at the sampling time t that has undergone consistency preprocessing, calculate the normalized weighting factor $w(i)$ according to (1), i = 1,2, … , n−c;

④ According to $\hat{x}_k = \sum_{i=1}^{n-c} w(i) x_i'$ calculate the first level fusion estimate of n−c historical observations after preprocessing of the kth sensor at sampling time t;

⑤ According to the same steps, calculate the first level fusion estimate of the historical observations of other m-1 sensors at the sampling time t;

⑥ On the basis of the first level fusion estimates of m sensors, the optimal weighting factor W_k^* of the kth sensor at sampling time t is calculated according to (11);

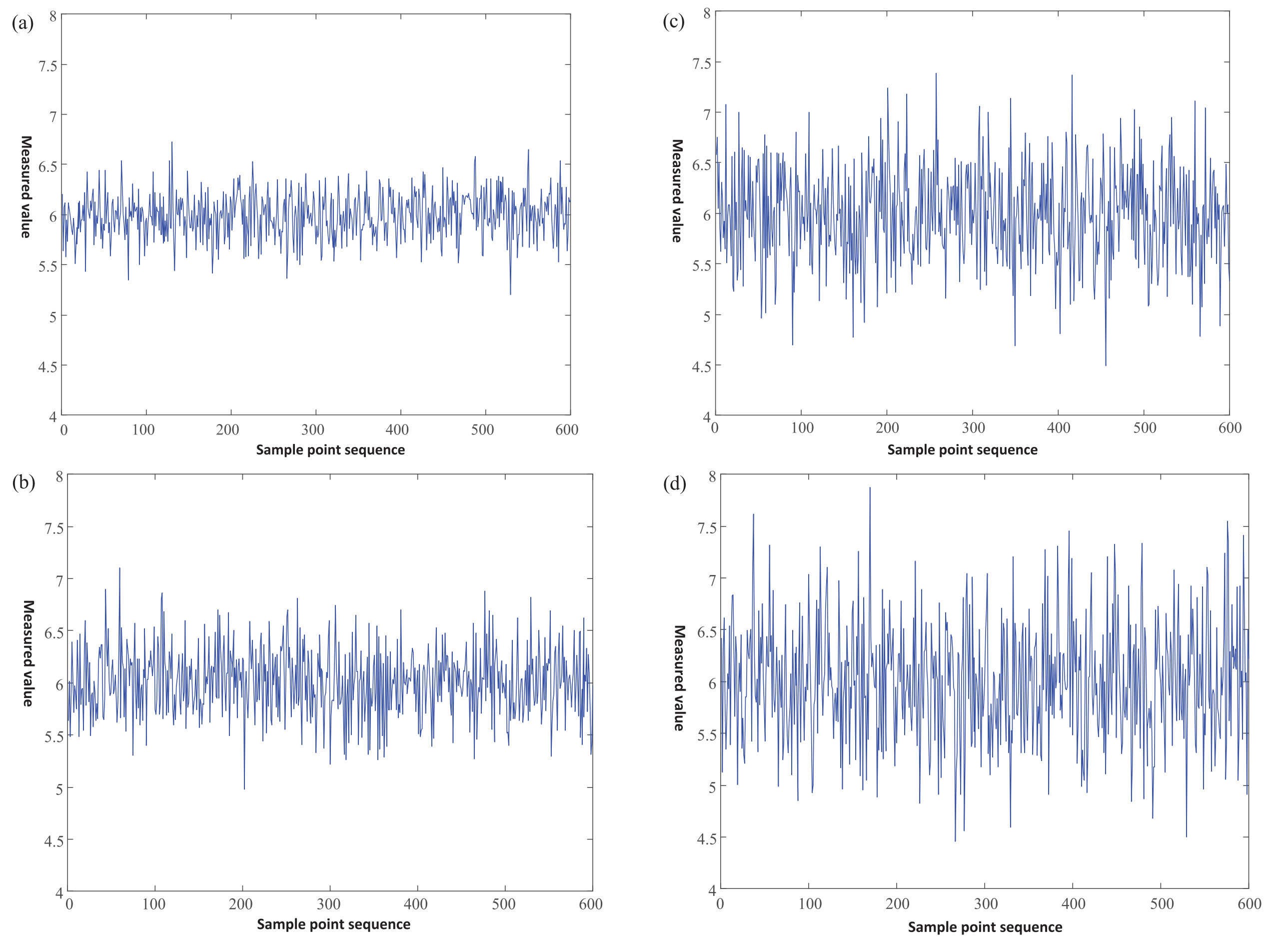

Figure 2. Four groups of measurement signal sequences buried by noise. (a) Output signal of sensor 1 (variance is 0.05); (b) Output signal of sensor 2 (variance is 0.1); (c)Output signal of sensor 3 (variance is 0.2); (d)Output signal of sensor 4 (variance is 0.3).

⑦ According to $\tilde{X} = \sum_{k=1}^{m} W_k \hat{x}_k$, calculate the second level fusion estimation of m sensors at the sampling time t, and the corresponding minimum mean square error can be calculated by (12).

III. Experiment and result analysis

According to the above two-level fusion algorithm flow of multi-sensor data based on off-centre distance and adaptive weighting, the simulation experiment is carried out with Matlab software. In the experiment, the number of sensors is 4, and the measured data sample length of each sensor is 600. Assuming that the true value to be estimated is $X = 6$, four groups of unrelated zero mean white noise data are used as the measurement errors of each sensor, and the variances of the four groups of measurement data are 0.05, 0.1, 0.2, and 0.3 in turn.

Four groups of measurement signal sequences with noise are shown in Figure 2.

The corresponding variance curve of each group of measurement signal sequence is shown in Figure 3.

For four groups of measurement signal sequences, the signal sequences after consistency preprocessing and single sensor weighted fusion are shown in Figure 4.

The method proposed in this paper is compared with the adaptive weighting method, and data fusion is performed on four groups of measurement signal sequences. The measurement estimation curve

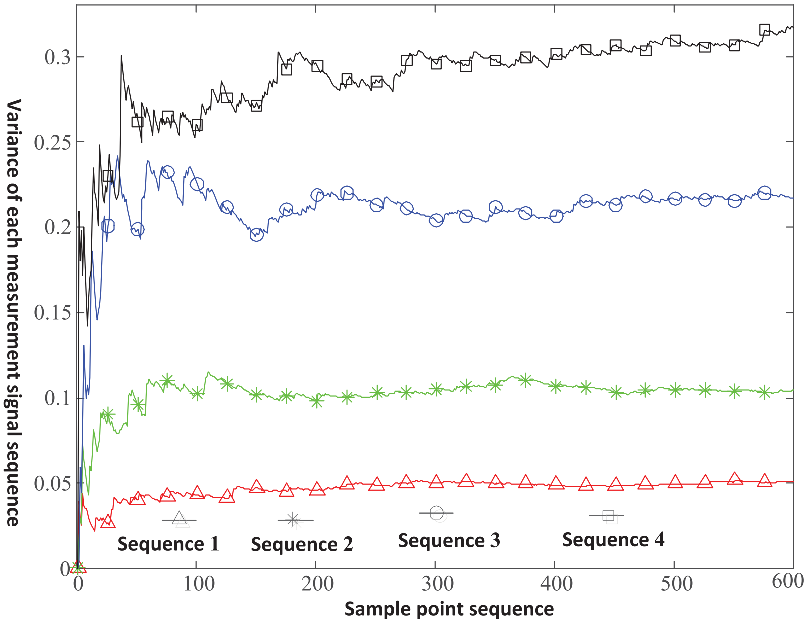

Figure 3. The variance curve of each signal sequence.

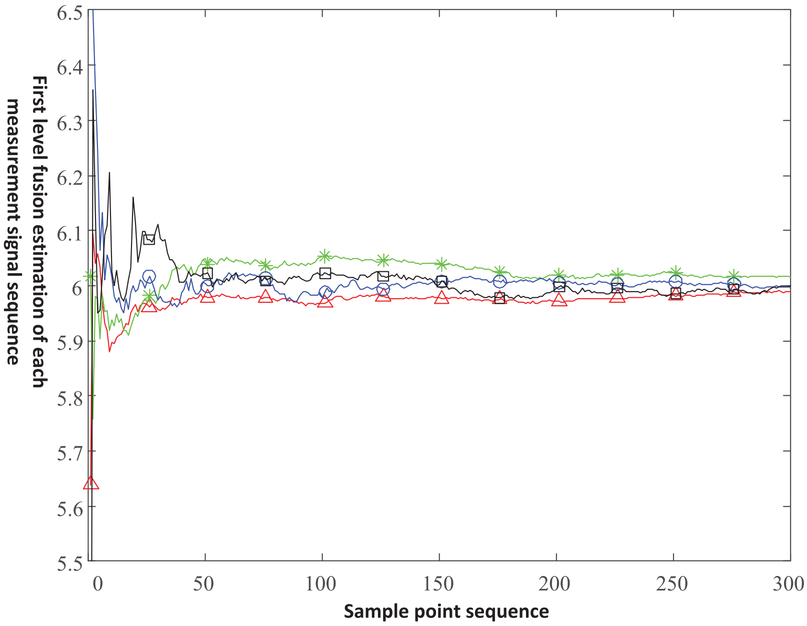

Figure 4. The measurement signal sequences of four sensors after single sensor weighted fusion.

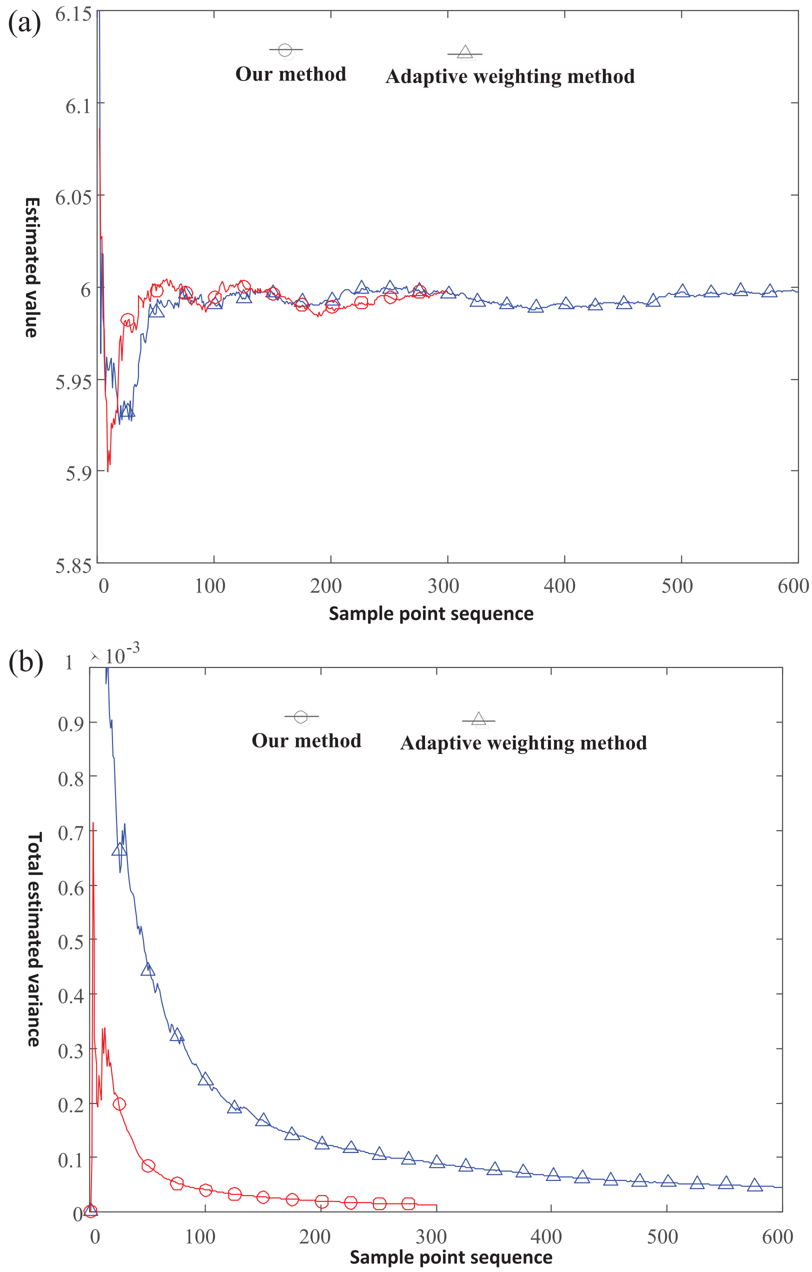

Figure 5. The optimal estimation curve and the variance curve of the optimal estimation of our method and adaptive weighting method. (a) The optimal estimation curve of the signal; (b) The variance curve of the signal optimal estimation.

obtained is shown in Figure 5, where Figure 5 (a) is the obtained optimal estimation curve of the measurement signal, and Figure 5 (b) is the total variance curve of the optimal estimation of the signal.

Figure 4 and Figure 5 show that since the method in this paper has carried out consistency pre-processing, and 50% of the sample data with large deviation from the centre distance is eliminated during pre-processing, the sample data length becomes shorter, which reduces the amount of calculation of the adaptive weighting later, and improves the time efficiency of the method. At the same time, it can be seen from the simulation results in Figure 5, that the total mean square error of the multi-sensor data secondary fusion algorithm based on off-centre distance and adaptive weighting is smaller than the total mean square error of the adaptive weighting fusion algorithm, and the convergence speed is faster. Compared with the adaptive weighting method, the estimated value curve obtained by our method is more stable, and the total estimated variance is smaller.

As shown in Table 1, in the experiment it is calculated that the average variance of the optimal estimation signal sequence of the proposed method is 0.000189, the average variance of the adaptive weighting method is 0.000057, and the corresponding variance of the average method is 0.0402. Compared with the adaptive weighting method and the average value method,

Table 1. The comparison of average variance of three methods.

Average value method	Adaptive weighting method	Our method
0.0402	0.000189	0.000057

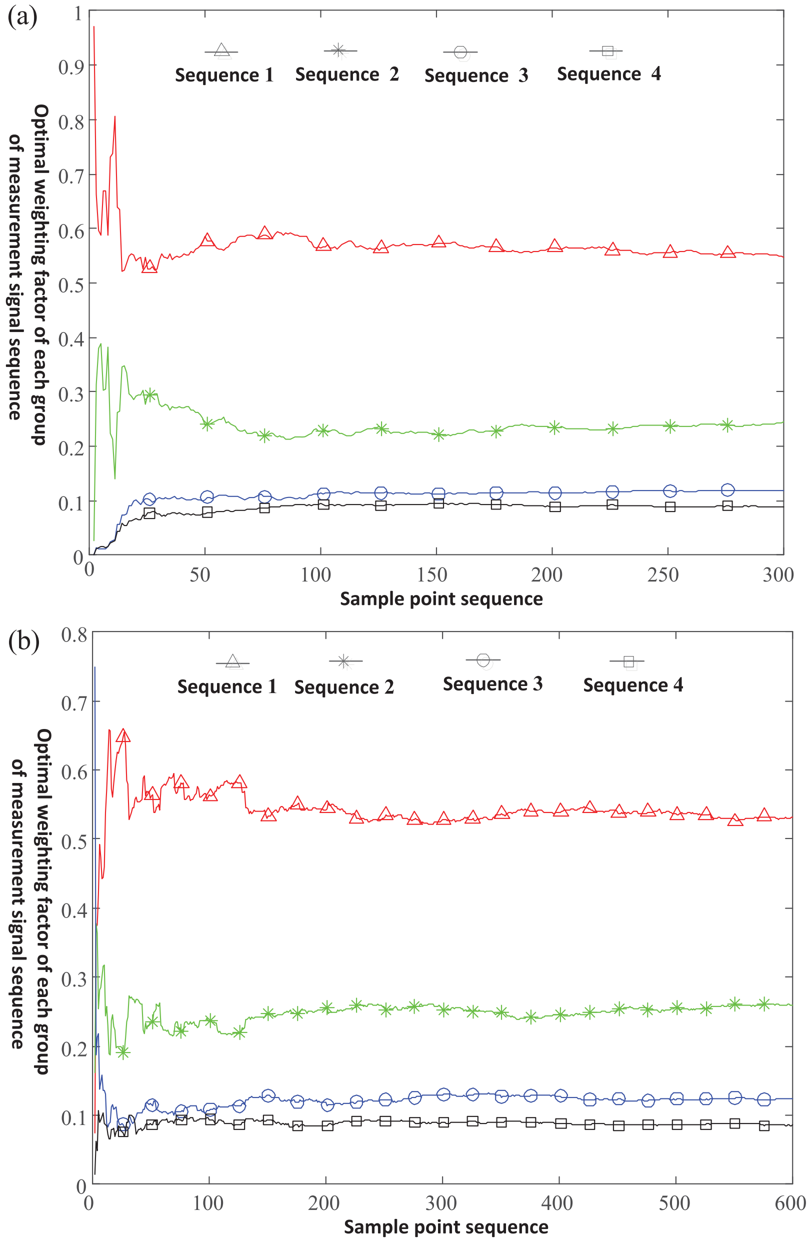

Figure 6. The optimal weighting factor curves of four groups of signal sequences of our method and adaptive weighting method. (a) The optimal weighting factor curve of each signal sequence in our method; (b) The optimal weighting factor curves of signal sequences in the adaptive weighting method.

our method can obtain more reliable signal estimation, and this algorithm does not require any prior knowledge, and can be realized only by using the historical measurement data of the sensor.

The optimal weighting factor curve of the four groups of measurement signal sequences of the method in this paper and the adaptive weighting method are shown in Figure 6.

It can be seen from Figure 3 and Figure 6 that the method in this paper is the same as the adaptive weighting method, which can make the weighting factor smaller corresponding to the signal sequence with larger variance, and the weighting factor larger corresponding to the signal sequence with smaller variance, so better signal estimation can be obtained. Because both methods determine their weights according to the variance of each sequence, the optimal weighting factor curves of the two methods are very similar in the experiment.

IV. Discussion

For multiple sets of measurement signal sequences obtained from a multi-sensor system, to reduce the random error of accompanying measurement data and improve measurement accuracy, in this paper a multi-sensor data fusion estimation algorithm based on consistency preprocessing and adaptive weighting is proposed. This algorithm does not require prior knowledge of sensor measurement data, but only relies on historical measurement data to optimize and estimate the measurement signal. This algorithm first preprocesses the consistency of a single sensor measurement signal sequence using the off-centre distance method, calculates the weighting factor of each measurement data, and then performs weighted fusion on the measurement signal sequence; Secondly, for multiple sets of measurement signal sequences from multiple sensors, adaptive weighted data fusion is proposed based on the principle of optimal weight allocation. In the experimental section, the proposed method was compared with the adaptive weighting method and the arithmetic mean method. The results show that compared with the adaptive weighting method and the arithmetic mean method, the proposed algorithm has a smaller mean square error, which can effectively improve the accuracy of data measurement, reduce redundancy, and can improve the stability of data measurement.

Future research will focus on two aspects. On the one hand, the method proposed in this article will be applied to other multi-sensor information collection systems, such as using wireless sensor networks for fire monitoring, temperature monitoring, etc., to test the feasibility and effectiveness of the method; On the other hand, studying how to combine homogeneous and heterogeneous data fusion algorithms to fully utilize effective data information and improve the comprehensive processing ability of algorithm is another issue that needs to be addressed in future research.

Disclosure statement

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