A multi-sensors weighted data fusion method based on measurement traversal correction

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Abstract: In the case of multi-sensors weighted data fusion with unknown prior knowledge, a weighted data fusion method based on measurement traversal correction is proposed. The fusion accuracy of multi-sensors data fusion is influenced by both the measurement data accuracy and the data fusion weights of sensors. The measurement data of sensors is corrected through analyzing the reliability of different time data measured by sensors. The fusion weights of multi-sensors data fusion are optimal through deeply analyzing the influence of weight distribution on multi-sensors data fusion accuracy. Typical examples are used to validate the proposed fusion algorithm, and the result shows that the fusion result is satisfying, and the algorithm is theoretical and practical.

1. Introduction
With the continuous development of information processing technology, multi-sensor information fusion technology has been widely used in many fields such as fault diagnosis, pattern recognition, and remote sensing detection. Using multiple sensors to measure the same parameter from different angles, the more complete the index data is obtained, the more accurate it is after fusion, and the higher the credibility is. There are many methods for data fusion. Compared with Bayesian decision-making and neural network and other fusion technologies, the subjective arbitrariness and the limitations of modeling are relatively large. The weighted fusion method [1-9] does not require prior information and has higher fusion accuracy. The advantages of the company have received widespread attention. The weighted fusion method in this paper fully considers the factors that affect the accuracy of multi-sensor data fusion. By analyzing the reliability of the measurement data of a single sensor, the sensor measurement data is traversed and corrected. Based on the corrected data the optimal weight distribution principle is used in Multi-sensor data fusion.

2. Sensor data preprocessing.
Assuming that independent sensors measure a certain characteristic parameter, the measurement equation is

$$\hat{x}_i(k) = x + \delta_i(k)$$

Where $\hat{x}_i(k)$ is the measured value of the parameter obtained by the first i-th sensor at the k time, $x$ is the true value of the parameter, $\delta_i(k)$ is the measured noise of the i-th sensor at the k time, and $\sigma_i^2$ obeys a Gaussian distribution with a mean value of zero and a variance of $\sigma_i^2$, $\delta_i \sim N(0, \sigma_i^2)$.

For each sensor, the accuracy of each measurement value is directly related to the accuracy of subsequent multi-sensor data fusion. Therefore, the reliability of sensor measurement values must be...
processed before data fusion to obtain more accurate data.

Assume that sensor i acquires a total of M measured values \( \{ \hat{x}_i(k) \}_{k=1}^{M} \) at the time T. From equation (1), it can be seen that the measured value of the sensor obeys the Gaussian distribution with mean \( \hat{x}_i \) and variance \( \sigma_i^2 \), \( \hat{x}_i \sim N(\hat{x}_i, \sigma_i^2) \).

According to the maximum likelihood function, the estimation of mean value \( \tilde{x} \) and variance \( \tilde{\sigma}_i^2 \) are as follows:

\[
\tilde{x}_i = \frac{\sum_{k=1}^{M} \hat{x}_i(k)}{M} \quad (2)
\]

\[
\tilde{\sigma}_i^2 = \frac{1}{M-1} \sum_{k=1}^{M} (\hat{x}_i(k) - \tilde{x}_i)^2 \quad (3)
\]

Since the value of sensor i at the time T obeys the normal distribution \( \hat{x}_i \sim N(\tilde{x}, \tilde{\sigma}^2) \), the probability that the measured value \( \hat{x}_i(k) \) of sensor i at the time k will occur as follows according to the concept of probability density:

\[
f(\hat{x}_i(k)) = \frac{1}{\sqrt{2\pi\tilde{\sigma}}} \exp\left\{ -\frac{1}{2} \left( \frac{\hat{x}_i(k) - \tilde{x}}{\tilde{\sigma}_i} \right)^2 \right\} \quad (4)
\]

According to formula (4), it can be known that the probability of occurrence of the measured value before the time k of sensor i is \( f(\hat{x}_i(j)) \) \( (1 \leq j < k) \).

When the measured value of sensor i at time k is corrected, the weight distribution of the measured value at each time and the corrected value of sensor i at time k can be expressed as follows:

\[
\omega_i(j) = \frac{f(\hat{x}_i(j))}{\sum_{j=1}^{k} f(\hat{x}_i(t))} \quad (5)
\]

\[
x_i(k) = \sum_{j=1}^{k} \omega_i(j) \cdot \hat{x}_i(j) \quad (6)
\]

3. Multi-sensor data fusion algorithm.

(1) For the measurement value \( \hat{x}_i(k) \) of sensor i at time k, the measurement values \( \{ \hat{x}_i(j) \}_{j=1}^{k} \) of the sensor before and at time k are used as a set of data for statistical analysis. By use of equations (2), (3), (4), (5) (6), the data of sensor i at time k is corrected. When the time \( k = 1 \), the correction value is equal to the measurement value. When the data of time \( k + 1 \) is corrected, the corrected data \( x_i(k) \) of time k is used.

\[
x_i(k) = \begin{cases} 
\hat{x}_i(k) & (k = 1) \\
\sum_{j=1}^{k-1} \omega_i(j) \cdot x_i(j) + \omega_i(k) \cdot \hat{x}_i(k) & (k > 1)
\end{cases} \quad (7)
\]

(2) Based on the M correction values \( \{ x_i(k) \}_{k=1}^{M} \) of sensor i at time T and optimal weighting principle, the weight value of sensor i for multi-sensor data fusion are as follows by use of equations (2) and (3).

\[
\omega_i = \left( \frac{1}{\tilde{\sigma}_i^2} \right) / \sum_{j=1}^{N} \left( \frac{1}{\tilde{\sigma}_j^2} \right) \quad (8)
\]
On the basis of steps (1) and (2), the fusion data of N sensors is as follows by use of the weight of sensor \(i\) to participate in data fusion \(\omega_i\) and the correction value \(x_i(k)\).

\[
y(k) = \sum_{i=1}^{N} \omega_i \cdot x_i(k)
\]  

(9)

4. Algorithm verification.

In order to verify the applicability of the algorithm in this paper to multi-sensor data fusion, this paper uses the example in the literature [1-3] as the verification example of this paper. The target true value is 900. Three thermocouples detect the temperature value of the incubator 6 times as Table 1 shows. At the same time, in order to compare the fusion effects of different fusion methods, this paper refers to the concept of standard deviation to define the fusion accuracy as:

\[
\sigma = \sqrt{\frac{1}{m-1} \sum_{i=1}^{m} (y(i) - 900)^2}
\]  

(10)

In the formula, \(\sigma\) represents the fusion accuracy, \(m\) represents the number of samples, and \(y(i)\) represents the first \(i\)-th fusion data.

### Table 1 The observed value of sensors

| Observation | sensor | Number of observations |
|-------------|-------|------------------------|
|             | 1     | 2  | 3  | 4  | 5  | 6  |
| 1           | 899.5 | 905.3 | 901.9 | 900.6 | 889.9 | 899.4 |
| 2           | 898.3 | 875.9 | 888.1 | 886.2 | 907.5 | 904.4 |
| 3           | 896.7 | 906.8 | 898.2 | 904.0 | 896.4 | 891.6 |

Since the fusion effect of the algorithm in the literature [1-4] has been confirmed that the fusion effect of the literature [3] is better, this paper uses the algorithm in the literature [3] as one of the algorithms for comparative analysis. In order to facilitate the comparative analysis between algorithms, the arithmetic average method is defined as algorithm 1, the algorithm in document [3] is defined as algorithm 2, and the approximate optimal weighted fusion algorithm is defined as algorithm 3.

The specific steps of Algorithm 3 are:

1. According to formula (2) and formula (3), the mean value \(\bar{x}\) and variance of the measured value \(\sigma_i^2\) can be obtained.

2. The fusion data of sensors can be obtained based on the principle of optimal weight distribution.

Using the fusion algorithm proposed in this paper, the fusion data are shown in Table 2. At the same time, Table 2 also lists the fusion results of Algorithm 1, Algorithm 2 and Algorithm 3 and the comparison of absolute errors. The total absolute error and fusion accuracy of the 6 fusion results of the 4 methods are reflected in Table 3.

### Table 2 Fusion results of 4 methods

| Observation frequency | Algorithm 1 absolute error | Algorithm 1 absolute error | Algorithm 2 absolute error | Algorithm 2 absolute error | Algorithm 3 absolute error | Algorithm 3 absolute error | Algorithm 3 absolute error |
|-----------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| 1                     | 898.1667                  | 1.8333                    | 898.1668                  | 1.8332                    | 898.2039                  | 1.7907                    | 898.7790                  | 1.2210                    |
| 2                     | 896.0000                  | 4.0000                    | 901.7699                  | 1.7699                    | 903.3237                  | 3.3237                    | 901.5305                  | 1.5305                    |
| 3                     | 896.0667                  | 3.9333                    | 900.0086                  | 0.0086                    | 899.1098                  | 0.8902                    | 900.2822                  | 0.2822                    |
| 4                     | 896.9333                  | 3.0667                    | 900.5356                  | 0.5356                    | 900.7592                  | 0.7592                    | 900.2907                  | 0.2907                    |
Table 3 The contrast of fusion effect

| Algorithm | Total absolute error | Fusion accuracy |
|-----------|----------------------|-----------------|
| 1         | 16.4333              | 3.1893          |
| 2         | 11.0776              | 2.4857          |
| 3         | 16.0068              | 3.4946          |
| Algorithm | 3.9221               | 0.1273          |

From Table 2 and Table 3, the fusion results and fusion effects of different algorithms can be seen:

(1) The overall fusion effect of Algorithm 2 is better than Algorithm 1 and Algorithm 3, but it is not completely better than Algorithm 1 and Algorithm 3 in terms of the accuracy of the fusion value at different observation times. This is because when the three methods use the same fusion data, the determination of the weight in Algorithm 2 takes into account the relationship before and after the sensor observation data, and results in the determination of the weight more reasonable than Algorithm 1 and Algorithm 3.

(2) The algorithm in this paper is superior to the other three algorithms in terms of the accuracy of the fusion result at the local observation time and the overall fusion effect. For example, in terms of total absolute error, the algorithm in this paper reduces 76% compared with algorithm 1, 65% compared to algorithm 2, and 75% compared with algorithm 3. In terms of fusion accuracy, the algorithm in this paper reduces 96% compared with algorithm 1, compared with algorithm 2 by 95%, and compared with algorithm 3 by 96%. The main reason is that the algorithm in this paper focuses on the reliability of sensor data at different observation moments. Through in-depth analysis of the sensor data at the current and historical moments, the overall accuracy of the sensor data is calculated, and the original sensor data is corrected with more accurate data. The second is that the algorithm in this paper uses the corrected data to allocate the optimal weights.

For the convenience of visual display, the comparison between the original observation data of each sensor and the sensor data corrected by this algorithm are reflected in figure 1.

![Fig.1 The contrast of sensor data before and after correction](image)

It can be clearly seen from Figure 1 that the original observation data of the three sensors are relatively scattered. If the the original observation data is directly used to participate in the data fusion,
the fusion effect is definitely not ideal. The corrected sensor data is relatively concentrated and is basically around the true value of 900, especially the sensor 1 and sensor 3. Although the corrected data of sensor 2 deviates from the true value of 900 to a certain extent, it has a relatively high credibility relative to the original data.

In order to reflect the stability of the method in this paper, the data in Table 1 is taken as a group, and 100 groups of repeated experiments are performed, and then the total absolute error and fusion accuracy of each group of fusion values are counted. The simulation result is shown in Figure 2.

![Fig.2(a) The simulation results of 100 groups of experimental total absolute error](image)

![Fig.2(b) The simulation results of 100 groups of experimental fusion accuracy](image)

It can be seen from Figure 2 that the total absolute error tends to decrease as the number of experimental groups increases, and finally stabilizes to about 0.3; the fusion accuracy first increases and then decreases as the number of experimental groups increases, and finally stabilizes Tend to 0.155.
5. Conclusion.
The key to the weighted fusion of multi-sensor data is to reasonably determine the fusion weight of sensor data and ensure the accuracy of sensor data measurement. This article mainly discusses the weighted fusion problem from the accuracy of sensor data and the reasonableness of weights. From the results of the calculation example, the method proposed in this paper can solve the problem of multi-sensor data fusion, and the method is relatively simple to program and easy to apply in engineering.

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