Online Fusion Method for Homogeneous Multi-sensor Based on Improved Fuzzy Clustering

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***Abstract*—Aiming at the problem of data fusion of the same unknown target in the isomorphic multisensor system without prior knowledge and without system model, an online fusion method based on improved fuzzy clustering is proposed. This method uses the robust fuzzy clustering method introduced into the noise class to analyze the multi-source data at the same time, avoids the dependence on the clustering number setting in the traditional fuzzy clustering fusion method, and can effectively remove the data source with large systematic offset And abnormal signals on the fusion result of the adverse effects; By introducing the influence factor of membership function and increasing the guidance of the historical fusion result on the current fusion, it is possible to reduce the possibility of the iterative calculation falling into the local extreme and improve the fusion accuracy. Simulation results show that this method has more advantages in terms of system adaptability and fusion accuracy than the traditional adaptive weighted average and clustering fusion method.**

***Index Terms*—robust fuzzy clustering, FCM clustering, multi-sensor, data fusion**

I. INTRODUCTION

Multi-sensor measuring and sensing system is a multi-level and multi-granularity complex information processing system integrating target measurement, data processing and information fusion. It is widely used in industrial system monitoring [1, 2], fault diagnosis [3], spatial location [4, 5], environmental observation [6, 7] and many other fields. At the data layer, the problem of homology-oriented multi-sensor perceptual sequence fusion is one of the most important contents in multi-sensor data fusion [8]. A sensing system composed of multiple identical sensors measures a parameter of the same measurement target to avoid measurement failure or distortion of a single sensor system due to a system failure and to improve measurement accuracy. However, in practical applications, the measurement results of many peers of the same kind are greatly affected by the difference of performance parameters of the sensor device itself and outside interference [9] ; In addition, the limited computing power of the sensing node and the real-time online The demand for analysis objectively limits the effective application of traditional fusion methods. Therefore, it is of great realistic and practical value to develop a data fusion method with simple computation, application on line, and high adaptability and fusion accuracy.

The traditional fusion methods for the same type of multisensor-based perceptual sequence are many, which are mainly summarized as weighted average [9,10,11], Bayesian estimation [12,13], maximum likelihood estimation[14], Kalman filter [15], neuronal networks [16], fuzzy logic[17,18] and other methods. Among them, the weighted average method is particularly suitable for the homogeneity of multi-sensor fusion in the data layer, but the weight distribution of the fusion effect is very obvious[11]; Bayesian estimation, maximum likelihood estimation and other statistical-based methods need to know the target's statistical prior knowledge; Bayesian estimation, maximum likelihood estimation and other statistical-based methods need to know the target's statistical prior knowledge; Kalman filtering requires knowledge of the system's mathematical model and noise statistics[15] and can not deal with the problem of adding sensors; The fusion method based on neural network needs training and learning process, the amount of computation increases with the input dimension and the number of neurons in hidden layer, and it also does not apply to the change with the input source; The fusion method based on fuzzy C-means clustering [19] directly combines the same kind of multi-sensor data with the advantages of simple calculation, no prior knowledge and limitation of system model, and can be applied online. However, the fusion results depend on clustering the number of determined is accurate.

Based on the above analysis, aiming at the problem of on-line fusion of the same-isomorphic multi-sensor perceptual sequence under the condition of no-priori and no-system model in unknown target perceptual measurement, this paper proposes an online fusion method based on improved fuzzy clustering. The method avoids the dependence on the clustering number setting in the traditional fuzzy clustering fusion method and can effectively remove the bad influence of the data source and the abnormal signal with large offset on the fusion result. At the same time, the guidance of the current integration through the historical fusion results has further enhanced the stability and accuracy of the integration. At the same time, the guidance of the current integration through the historical fusion results has further enhanced the stability and accuracy of the integration. Simulation results show that this method has better fusion accuracy and robustness than traditional adaptive weighted average and clustering methods. At the same time, the method has the advantages of simple calculation, online application, not limited by the number of sensors and the like, and thus has good adaptability and practical value.

II. FUSION MECHANISM ANALYSIS

The errors that the sensor device produces in the measurement mainly include systematic error, stochastic error and coarse error three kinds [20]. Suppose $Z_i^{(t)}$ is the observed value of the system at time t, $\bar{X}^{(t)}$is the real value of the measured parameter, $X_i^{(t)}$is the measured value of sensor I, there is:

$$Z_i^{(t)} = X_i^{(t)} + v_i^{(t)} + n_i^{(t)} + \omega_i^{(t)} \quad (1)$$

$$X_i^{(t)} = \bar{X}^{(t)} + v_i^{(t)} \quad (2)$$

Among them, $v_i^{(t)}$ is a systematic error, usually manifested as a measure of the actual value in a certain direction there is a regular offset; $n_i^{(t)}$ is a random error, usually subject to some statistical rules; $\omega_i^{(t)}$is a coarse error, with a large sporadic. We assume that the systematic random error obeys the zero-mean normal istribution, is $n_i^{(t)} \sim N(0, \sigma_i^2)$, for the same target measured by multiple sensors of the same type, the observed values $Z_i^{(t)} \sim N(X_i^{(t)}, \sigma_i^2)$ can be approximated. In the actual measurement, different sensor observations $\boldsymbol{Z}^{(t)} = \left\{Z_1^{(t)}, Z_2^{(t)}, \cdots, Z_m^{(t)}\right\}$'s distribution can be represented by "Fig. 1."

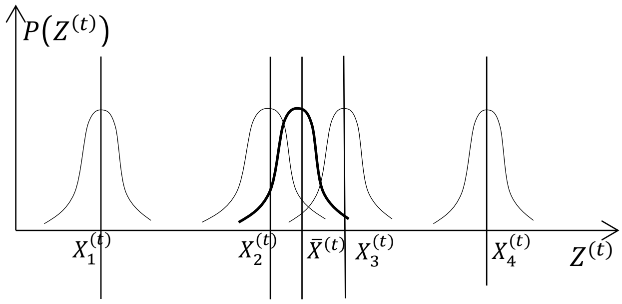


Figure 1. Observations distribution map of the homogeneous multi-sensors

It can be seen from Fig. 1 that most of the $X_i^{(t)}$ "gather" are centered on the closer area of $\bar{X}^{(t)}$ and the distance $\bar{X}^{(t)}$,the most of $v_i^{(t)} \to 0$; Only a small number of sensors due to failure and other reasons, so that $|v_i^{(t)}| > \varepsilon$.

Based on the above assumptions, the conception of fusion is given as follows: the fuzzy clustering is performed on the observed values of each sensor at time t, and most of the observations closer to $\bar{X}^{(t)}$ are grouped and merged deal with; Observations that are farther from $\bar{X}^{(t)}$ are considered as abnormal measurements and as outliers do not participate in fusion calculations. Through the above measures, the adverse effect of the observation value far from the true value on the fusion result is effectively avoided.

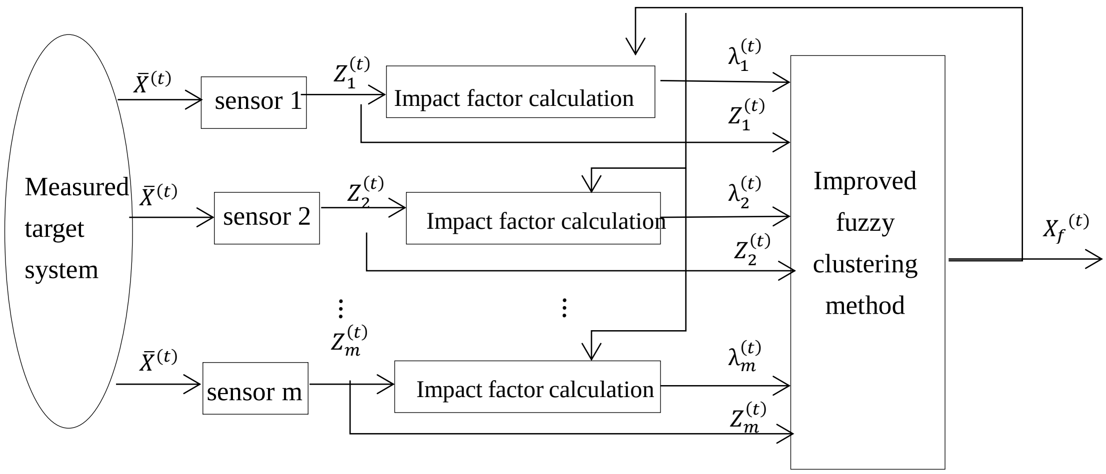


Figure 2. Structure of the data fusion method based on advanced fuzzy clustering

III. FUSION METHOD BASED ON IMPROVED FUZZY CLUSTERING

A. Fusion Architecture

The proposed integrated fusion architecture based on improved fuzzy clustering data fusion method is shown in Fig.2. The measured target is a certain attribute parameter that is measured by multiple sensors to form multiple observations(between $Z_1^{(t)}$ and $Z_m^{(t)}$). After the current observed value and historical data, historical fusion results and other data after the statistical weight calculation, the formation of impact factors $\lambda_i^{(t)}$ based on statistical weights. The improved fuzzy clustering method was used to calculate the observed values of each sensing source and the calculated influencing factors by fuzzy clustering to obtain the fusion result. The measured target is a certain attribute parameter that is measured by multiple sensors to form multiple observations.

B. statistical weight calculation

The traditional methods of homology and isomorphism multi-sensor data fusion are all based on the analysis of multi-source datasets at the moment [19]. However, in the process of actual integration, the relationship between historical data and historical fusion results can largely reflect the size and distribution of the differences between observations and fusion results of each sensor source. Taking into account these rules for the fusion of the next moment has a guiding role, so the introduction of historical data based on historical fusion results and the statistical weight λ. Let $\boldsymbol{Z}_i^L = \left\{Z_i^{(t-1)}, Z_i^{(t-2)}, \cdots, Z_i^{(t-L)}\right\}$ be the set of historical observations at time L before t; Let $\boldsymbol{X}_f{}^L = \left\{X_f{}^{(t-1)}, X_f{}^{(t-2)}, X_f{}^{(t-3)}, \cdots, X_f{}^{(t-L)}\right\}$ be the set of fusion results at time L before t. The sensor fusion variance is calculated as follows:

$$\sigma_i = \sqrt{\frac{1}{L}\sum_{j=1}^{L}\left(Z_i^{(t-j)} - X_f{}^{(t-j)}\right)^2}, (\ i = 1,2,\cdots,m) \quad (3)$$

Iteration calculation formula is as follows:

$$\left[\sigma_i^{(t)}\right]^2 = \left[\sigma_i^{(t-1)}\right]^2 + \frac{1}{L}\left[\left(Z_i^{(t-1)} - X_f{}^{(t-1)}\right)^2 - \left(Z_i^{(t-L-1)} - X_f{}^{(t-L-1)}\right)^2\right] \quad (4)$$

Each sensor statistical weight $\lambda_i^{(t)}$ is calculated as:

$$\lambda_i^{(t)} = \frac{1}{\left[\sigma_i^{(t)}\right]^2 \sum_{j=1}^{m}\frac{1}{\left[\sigma_j^{(t)}\right]^2}}, \ (i = 1,2,\cdots,m) \quad (5)$$

C. Fusion Method Based On Improved Robust FCM (RFCM) Clustering

1. RFCM Clustering Method

RFCM is a clustering method based on the traditional FCM, which is improved by introducing noise classes [21]. Let $X = \{x_1, x_2, \cdots, x_n\} \in R^S$ be a set of n arbitrary given data in S-dimensional space, $x_k (k = 1,2,\cdots,n)$ be a sample point; $P = \{C_1, C_2, \cdots, C_c\}$ is the set of c that the set X belongs to. The fuzzy class can be defined by the following class:

（1）$\forall x_k \in X\ and\ \forall C_i \in P, 0 \le \mu_{C_i}(x_k) \le 1.$

（2）$\forall x_k \in X, \exists C_i \in P, such\ that\ \mu_{C_i}(x_k) > 0.$

（3）$\forall x_k \in X, \sum_{i=1}^{c} \mu_{C_i}(x_k) = 1.$

In the formula, $\mu_{C_i}(x_k)$ is a membership function, which indicates that x_k belongs to the class C_i.
Define the objective function J_m as follows:

$$J_m(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(\mu_{C_i}(x_k)\right)^p (d_{ik})^2 \quad (6)$$

Among them, p is membership function index, $(d_{ik})^2 = \|x_k - v_i\|^2$, v_i is the i-th($i = 1,2,\cdots,c-1$) category center vector. For the noise class, that is the c-th class, there are:

$$d_{ck}^2 = \delta^2 \quad (7)$$

The parameter δ is the radius of the noise type, and the calculation formula in [22] can be chosen to realize automatic update:

$$\delta^2 = \rho\frac{\sum_{i=1}^{c-1}\sum_{k=1}^{n}(d_{ik})^2}{n(c-1)} \quad (8)$$

The membership function $\mu_{C_i}(x)$ and the cluster center v_i are iteratively calculated by the following formula:

$$\mu_{C_i}(x) = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x-v_i\|^2}{\|x-v_j\|^2}\right)^{1/p-1}}, \quad 1 \le i \le c, x \in X \quad (9)$$

$$v_i = \frac{\sum_{x\in X}\left(u_{C_i}(x)\right)^p \times x}{\sum_{x\in X}\left(u_{C_i}(x)\right)^p}, 1 \le i \le c. \quad (10)$$

2. Data Fusion Method Based On Improved RFCM Clustering

The main idea of data fusion algorithm based on fuzzy clustering is to classify the current multi-source perceptual data at the same time into two categories: normal class and bnormal class by using fuzzy clustering method. The center of normal class is calculated as the fusion result, and the abnormal data is not involved in the fusion calculation as fault data. The fuzzy clustering method adopted in the above mentioned RFCM clustering method introduces the statistical weight λ of the formula （5） to modify the membership function index. The objective function can be modified as follows:

$$J'_m(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{n}\left(\mu_{C_i}(x_k)\right)^{\mu_k}(d_{ik})^2 \quad (11)$$

$$\mu_k = p(1-\lambda_k) + \lambda_k \quad (12)$$

In the formula, μ_k is the adjusted membership function index. Due to the λ_k multiplier, μ changes in the interval (1, p), and $\left(\mu_{C_i}(x_k)\right)^{\mu_k}$ increases with increasing λ_k. This shows that the sensing source with smaller variance of historical data has a greater influence on the fusion result in the current fusion process, so as to achieve the purpose of the historical fusion result guiding the current fusion process.
Accordingly, the formulas (9) and (10) are amended as:

$$\mu_{C_i}(x_k) = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k-v_i\|^2}{\|x_k-v_j\|^2}\right)^{1/\mu_k-1}} \quad (13)$$

$$v_i = \frac{\sum_{k=1}^{n}\left(u_{C_i}(x_k)\right)^{\mu_k} \times x_k}{\sum_{k=1}^{n}\left(u_{C_i}(x_k)\right)^{\mu_k}} \quad (14)$$

Among them, $1 \le i \le c, 1 \le k \le n$. Fusion computing iterative process shown in Figure 3. The membership function matrix is initialized to$U_0 = [\lambda; (1-\lambda)]$.

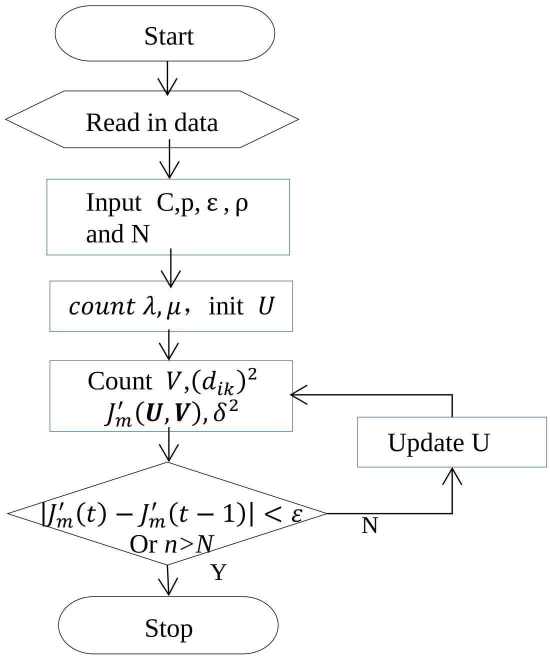


Figure 3. Fusion algorithm flow chart

IV. TEST VERIFICATION

A. Experimental Simulation

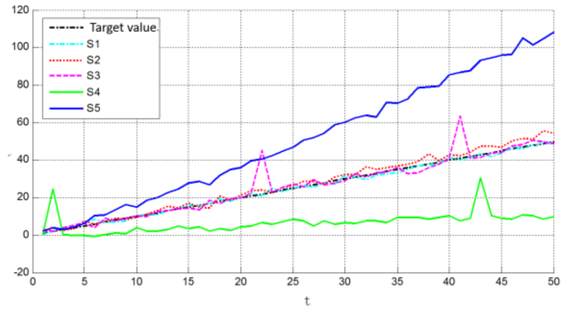
In order to verify the fusion effect of the proposed method, we use four sets of data to test the method respectively, and compared with adaptive weighted average and traditional FCM clustering fusion method to verify the effectiveness and superiority of the proposed algorithm.

Test one: The sample data generated by the multi-sensor mathematical model in [19] was used to simulate the test. The model consists of five sensing sources, the specific expression is as follows:

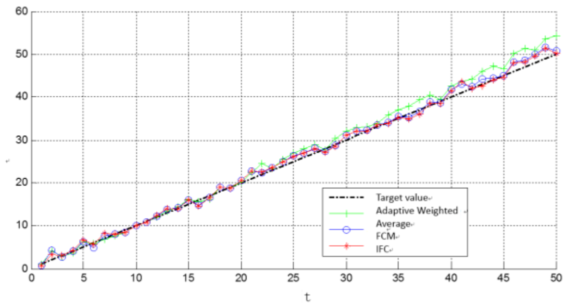
$$\begin{cases} S_1 = x + n_1 \\ S_2 = x^{1.02} + n_2 \\ S_3 = x + \sin(0.3x) + n_3 \\ S_4 = xe^{-0.003x} + n_4 \\ S_5 = x^{1.08} + n_5 \end{cases} \tag{15}$$

In the formula, S_i is the real measurement value of the i-th sensor, x is the actual value of the target object, n_i is random white noise, and the noise variance $\sigma^2 = 1.5$. In addition, two outliers are added to S_3 and S_4 respectively as gross errors. It can be seen that the sensors corresponding to S_4 to S_5 have some systematic errors.

The original data image and the application of three methods of fusion results image shown in Fig.4.”



(a) The sample data



(b) Fusion results for three different methods

Figure 4. The 1st group samples and comparison of fusion results

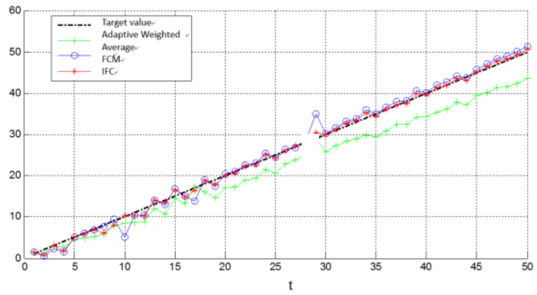
It can be seen from “Fig. 4 (a)” that as time increases, S_4 and S_5 have larger systematic errors than S_1, S_2 and S_3, that is, Z_4 and Z_5 are far away from the real value in different directions at the same time t. In Figure 4 (b), before t = 25, the fusion effects of the three methods are all ideal. However, with the increase of the distance between Z_4, Z_5 and real value after t = 25, the fusion error of adaptive weighted averaging method is larger than that of the other two methods, which shows that this method is greatly affected by the "anomaly" of the sensing source . In addition, Figure 4 (b) also shows that the three fusion methods are not sensitive to gross errors.

Test two: The multisensor mathematical model with obvious classification features was used to test the system error. The specific model is as follows:

$$\begin{cases} S_1 = x + n_1 \\ S_2 = x^{1.02} + n_2 \\ S_3 = x + \sin(0.53x) + n_3 \\ S_4 = 0.35xe^{-0.003x} + n_4 \\ S_5 = x^{0.8} + n_5 \end{cases} \quad (16)$$

The noise variance is $\sigma^2 = 1.5$, in addition, two outliers are added to S_3 and S_4 respectively as coarse errors. The original data image and application of three methods of fusion results image shown in “Fig. 5.”

(a) The sample data



(b) Fusion results for three different methods

Figure 5. The 2nd group samples and comparison of fusion

In “Fig.5 (a)”, the observed values Z_4 and Z_5 of S_4 and S_5 appear to be away from each other in the same direction and close to each other. Affected by this, in the fusion result of “Fig. 5 (b),” the adaptive weighted average fusion method shows a large fusion error after t = 10, and the error increases with time t. This shows that in the presence of one-sided systematic errors in a multi-sensor system, the adaptive weighted averaging method is more affected by the "anomaly" of the sensing source and distorts the fusion result. In addition, “Fig.5 (b)” also shows that the three fusion methods under this system are not sensitive to gross errors.

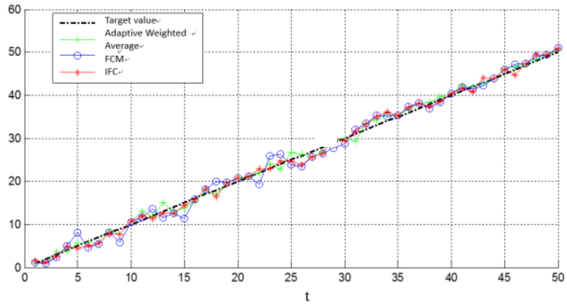
Test three: The test is carried out using a multisensor mathematical model with zero system error and different random errors. The specific expression of the model is as follows:

$$\begin{cases} S_1 = x + n_1 \\ S_2 = x + n_2 \\ S_3 = x + n_3 \\ S_4 = x + n_4 \\ S_5 = x + n_5 \end{cases} \quad (17)$$

Where $n_i (i = 1, \cdots, 5)$ corresponds to the variance of $\sigma_1^2 = 1.5$, $\sigma_2^2 = 3.0$, $\sigma_3^2 = 3.25$, $\sigma_4^2 = 4.5$ and $\sigma_5^2 = 5.25$. Also add two outliers to S_3 and S_4 respectively as gross errors.

The original data image and the application of three methods of fusion results of the image shown in “Fig. 6.”

(a) The sample data



(b) Fusion results for three different methods

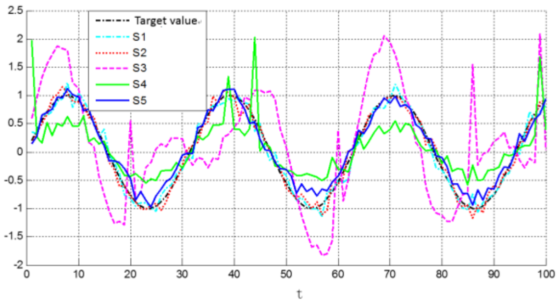
Figure 6. The 3rd group samples and comparison of fusion results

It can be seen from the fusion results in “Fig. 6 (b)” that under the premise of the systematic error of 0, the random error of different sizes and a certain gross error, all the three methods can obtain the fusion result consistent with the trend of the real value, the cumulative error is not particularly obvious distinction. Quantitative cumulative error analysis will be given later in the performance test.

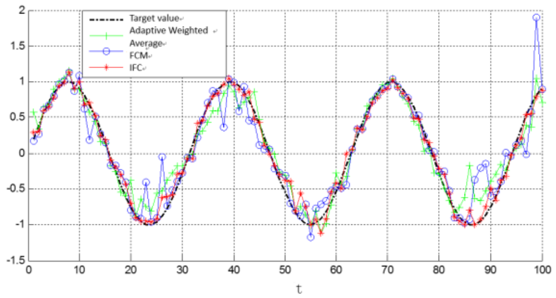
Test four: Testing with multi-sensor mathematical model with oscillatory characteristics ($\sigma^2 = 0.01$). The specific model is as follows:

$$\begin{cases} S_1 = \sin(0.2x) + n_1 \\ S_2 = \sin(0.2x)^{1.02} + n_2 \\ S_3 = \sin(0.2x) + \sin(0.3\sin(0.2x)) + n_3 \\ S_4 = \sin(0.2x)\, e^{-0.003\sin(0.2x)} + n_4 \\ S_5 = \sin(0.2x)^{1.08} + n_5 \end{cases} \quad (18)$$

Also add four outliers in S_3 and S_4 as coarse errors. The original data image and the application of three methods of fusion results image shown in “Fig. 7.”



(a) The sample data



(b) Fusion results for three different methods

Figure 7. The 4th group samples and comparison of fusion results

It can be seen clearly from “Fig. 7 (b)” that the improved fuzzy clustering fusion method can reflect the true value of the target more accurately, however, the fusion result of traditional FCM fusion method deviates far from the true value, indicating that there is a large fusion error.

B. Performance Analysis and Testing

First of all, from the mathematical principle level analysis of the impact of the three methods on the fusion accuracy. The determination of weights in the traditional adaptive weighted average fusion method is determined under the optimal condition that the total mean square error is the minimum. Obviously, when the multi-sensor system has only random errors, the fusion result obtained by the adaptive weighted averaging method has the smallest deviation from the true value and the best fusion result [8]. However, when there are obvious systematic errors with non-random characteristics between the sensors, the measured values of the various sensing sources are no longer unbiased estimates of the true values, therefore, the fusion result is necessarily larger than the true value, which is confirmed in Experiment II.

The fusion method based on fuzzy C-means clustering classifies each observation data by fuzzy clustering and takes the "big class" class centers containing multiple observations as fusion results [18]. Since the objective function of the fuzzy C-means clustering method is determined based on the minimum total variance rule (equation 6), therefore, under the conditions of only random error, the fusion result is also close to the true value. The advantage of this method is that it can eliminate the influence of the measurement with regular deviation on the fusion result, drawbacks are: 1) The determination of the number of classes directly affects the accuracy of the fusion results; 2) Analysis of the current results, can not consider and draw on historical experience results.

Based on the fuzzy C-means clustering fusion method, the proposed method solves the problem of determining the number of clusters by introducing noise classes, the influence of historical experience on the current computation is increased by introducing the influence factor of membership function into the current fusion, and to a certain extent, the fusion result (cluster center) is closer to the true value.

In order to quantitatively analyze the fusion accuracy of the algorithm, three different methods were used to perform fusion experiments on different 10 groups of data generated by the four models respectively, and the average fusion error $\bar{v}$ of the three methods was statistically calculated. The test results are listed in the following table:

TABLE I
COMPARISON OF MEAN FUSION ERROR OF THREE FUSION METHODS

	Model 1	Model 2	Model 3	Model 4
Adaptive Weighted Average	2.06	3.95	0.91	0.25
Traditional FCM clustering	1.18	1.08	1.62	0.31
Improve fuzzy clustering	1.04	1.06	1.21	0.18

As can be seen from Table I, for the four different types of system data, the improved fuzzy clustering fusion method proposed in this paper has higher fusion accuracy than the traditional FCM clustering fusion method; Although adaptive weighted averaging can achieve higher convergence accuracy in multi-sensor fusion without system error, however, for systematic errors with significant unidirectional offset, the fusion results will be significantly biased. Therefore, on the whole, the method proposed in this article has more advantages than the other two methods.

V. CONCLUSION

In order to meet the specific requirements of data fusion based on multi-sensor system composed of HOMS, this paper proposes an on-line fusion method of HOM based on improved fuzzy clustering. This method not only has the advantages of traditional data fusion methods based on FCM clustering without prior knowledge, without system model, support system expansion (sensor nodes increase and decrease), simple calculation and online application, by changing the fusion strategy and introducing noise class, the problem of setting the number of clusters in the traditional fuzzy clustering fusion method is effectively avoided, at the same time, the adverse effect of the data source and abnormal signal with large offset on the fusion result is effectively removed. The influence factor of membership function is introduced into the algorithm to increase the guidance of historical fusion on the current fusion, which avoids the blindness and randomness of initial parameter selection and helps to avoid the local extreme value problem and greatly reduce the iterative calculation time. The experimental results show that this method has better robustness and fusion accuracy than the FCM clustering fusion method, and has more adaptability than the traditional adaptive weighted average fusion method.

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