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Multi-Source Information Fusion Conflict Processing Algorithm in Internet of Things

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In view of the lengthy processing time of the traditional multi-source information fusion conflict processing algorithm, this paper studies this algorithm under the Internet of things. Firstly, multi-source information is extracted and registered, then conflict measurement standards are formulated and, finally, processing rules are determined to complete the processing of multi-source information fusion conflict. The experimental results show that the proposed algorithm has faster processing performance compared with the traditional method, giving it significant practical value.

Keywords: Internet of Things; Multi-Source Information Fusion; Conflict; Registration; Rules;

1. INTRODUCTION

In order to make the target information and identity recognition more accurate, information from multiple sensors of the same or different types undergoes comprehensive processing; this is termed 'information fusion'. Information fusion is applied to the processing of the original data layer, feature abstraction layer and decision layer. Accordingly, different mathematical algorithms are applied to solve the problems encountered during the fusion process. Because of the influence of the sensor's own performance, possible interference from elements in the external environment, and other problems, the data received by the sensor may be inaccurate. The fusion of multi-sensor information can help to address the problem of inaccuracy, and enable rational inferences and decisions to be made from the information obtained. Given the different methods of information fusion processing and analysis, information fusion systems can be divided into three types: space fusion, time fusion and space-time fusion. Space fusion refers to the information fusion processing and analysis of different sensor measurements simultaneously Time fusion refers to the information fusion processing and analysis of the same sensor measurements at different times. Spatio-temporal fusion refers to the continuous information fusion processing and analysis of the measured values of different sensors during a period of time. Moreover, the different methods used by an information fusion system for information processing and analysis, can be categorized into three types: distributed, centralized and hybrid. 'Distributed' means that each sensor processes and analyzes the measurement data separately, and then sends the results to the fusion center which in turn processes and analyzes the local results of each sensor. 'Centralized' means that the data from each sensor is sent to the central processor for information fusion processing and analysis. This method can achieve the integration of space and time, and the accuracy of the data processing is high. However, the amount of data transmitted is large, requiring a large communication bandwidth, and the data processing capacity of the central processor is high. Compared with centralized processing, distributed processing has the advantages of fast computing speed, good continuity and reliability, and low requirements for communication bandwidth. However, the accuracy is not as high as that of centralized processing. Hybrid processing

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is a combination of the first two methods, and is used in large-scale systems. According to the above analysis, in a complex environment, it is systematic, feasible and effective to acquire an overall understanding by using expert's domain knowledge. However, experts in different fields have different views on the conflict processing of multi-source information fusion, and the conclusions may be different, or uncertain. At the same time, the participation of more domain experts will lead to conflicts between expert opinions and increase the uncertainty of conclusions. How to deal with the conflict of multi-source information fusion effectively and evaluate it efficiently and reliably is a practical problem that must be solved. Therefore, this paper designs a multi-source information fusion conflict processing algorithm under the Internet of things. The Internet of things is the "Internet of everything", which is an extension and expansion network based on the Internet. It combines various information sensing devices with the Internet to form a huge network, achieving the interconnection of people, machines and things at any time and any place. The Internet of things is an important aspect of the new generation of information technology The core and foundation of the Internet of things is still the Internet, but is an extension and expansion network based on the Internet. At the user end, it extends and expands to any goods and information. Therefore, the Internet of things is a network that connects any object with the Internet for information exchange and communication through information-sensing devices such as radio frequency identification, infrared sensor, global positioning system, laser scanner, etc. according to the agreed protocol, so as to realize the intelligent identification, positioning, tracking, monitoring and management of the object of interest.

2. DESIGN OF CONFLICT PROCESSING ALGORITHM FOR MULTI-SOURCE INFORMATION FUSION UNDER THE INTERNET OF THINGS

2.1 Multi-Source Information Collection and Preprocessing

2.1.1 Multi-Source Information Extraction

In the process of multi-sensor information fusion, due to the existence of uncertain factors, the reliability of the information provided by each sensor is not equal. The sensor information that is very inconsistent with information received from most of the other sensors has low reliability and low weight, thereby reducing the impact on the fusion results. Information that is basically consistent with most other sensor information should be given a large weight [1], and its position among the combined evidence should be greater. Therefore, the data information extraction module extracts all environment information contained in the data table corresponding to the source database system according to the information provided by the mapping file, and outputs the data information extraction file to the document. The fusion system manages all kinds of sensor resources according to the working principle in order to ensure the best data acquisition performance. In the complementary system consisting of multiple sensors, when observing the same target set, it is necessary to coordinate and manage each sensor in the set, that is, the indication and handover management of multiple sensors. Different management methods will also affect the output information of the sensor so, for the complementary system comprising multiple sensors, in the game fusion [2–4], the different management methods of the sensor set can be used as strategies that can be adopted in the game fusion in the strategy extraction of the player. The game fusion model:

The steps required for data information extraction:

First, analyze the mapping file. Then, according to the information provided by the mapping file, determine the need to extract the field information of the data table from the source database system.

Second, according to the field information, generate the statement, send the statement to the source database system to execute the query and return to the dataset. In this system, the interface is used to access the database system. Finally, the returned data set is placed in the data structure to await processing.

Third, the data in the data structure is processed circularly, and the output results are sent to the XML document. The root element represents a data information extraction file. All environment information contained in each data table corresponding to the source database system corresponds to a sub-element in the XML document, and the text element represents the name of each data table corresponding to the source data mining database system. Each row of environmental information in each data table corresponds to a sub-element attribute, which corresponds to the field name and all environmental information contained in each data table.

Using the collected multi-source information as the resource base, the process of establishing the multi-evidence decision table is: set the time interval as 1, select the corresponding data at each time point as a row of the decision table.

Some of the selected data are listed in the following table:

In the table, a, b, c, and d represent four evidences and e represents the domain.

Then, by using the game fusion model, the sensors involved in conflict and cooperation are regarded as players. The method used to extract players is:

First, the complementary information in cooperation is regarded as people in different information bureaus. For example, the results of extracting people in information bureaus in conflict environment are as follows. The people in bureaus are recorded as $Q = |A_1, A_2|, B$. In this set, sensor A_1 information and sensor B information are complementary information, providing redundant information representation of the same target, but the purpose of the game is to make the whole system tend to entropy stability for this reason, A_1 and A_2 are regarded as different people in the information bureau.

Second, the redundant information in the conflict situation, the complementary information, and the redundant information, are all regarded as different agents.

2.1.2 Multi-Source Information Registration

Multi-sensor registration is a data processing action used to obtain error-free, measurement-conversion information. The main causes of measurement data errors are:

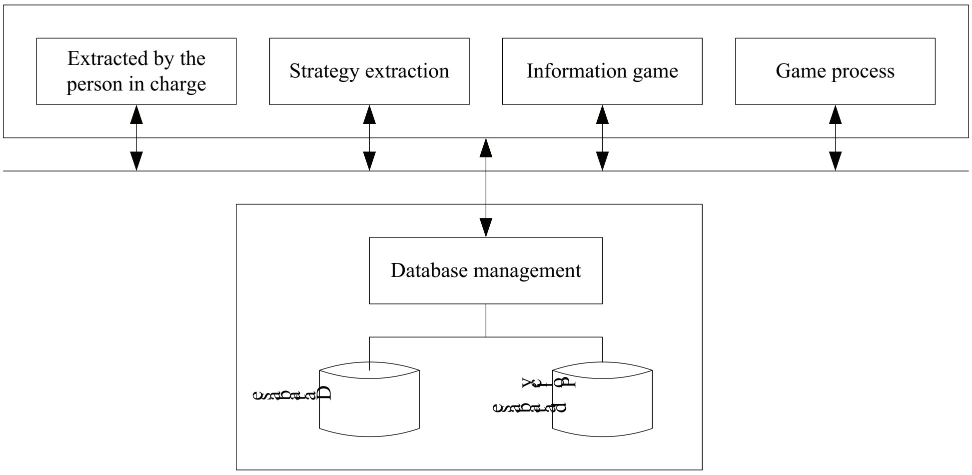

Figure 1 Functional model of game integration

Table 1 Multiple evidence decision table.

a	b	c	d	e
1	1	1	1	1
2	1	1	1	1
1	1	1	1	1
1	1	1	2	1
2	2	1	1	1
1	1	2	1	1
2	1	1	1	1
1	2	1	1	12
3	1	1	1	2
1	1	1	1	2
2	1	1	1	2
3	2	1	1	3
1	3	1	12	3
3	1	1	2	3
1	3	3	2	3
2	2	2	1	3
1	2	1	3	3

(1) the performance factors of the sensor itself; that is, there is a certain degree of deviation in the measurement data obtained by using the sensor;

(2) the deviation caused by the coordinate transformation of the measurement obtained by the sensor is mainly caused by the inertial sensor measuring instrument;

(3) the time error and position error of the information measured by the sensor in the standard coordinate system. The time error is caused by a different clock crystal and the position error is caused by the navigation system;

(4) the errors are caused by different local registration algorithms [5–8], that is, the errors of the whole track caused by different local track inaccuracies.

The time estimation method is used to determine the state of the target and, simultaneously, the deviation of the sensor system, which turns the problem into a time registration problem. Because in the information fusion system, the measurement of the target by the sensor system of each platform is independent, the sampling period of the sensor may be different, and the data transmitted by each subsystem, such as the fusion center, will create the phenomenon of apparent time mismatch. In addition, due to the delay of the communication network, a time error will occur between each platform sensor and the fusion center. Therefore, it is very important for the accuracy of the whole system to register an asynchronous sensor report in the fusion center as a synchronous sensor report. The registration algorithm based on the principle of interpolation and extrapolation is used to register the time in the same time segment. In this time segment, the measurement data collected by the sensor is interpolated and extrapolated in order to extrapolate the high-precision time data to the low-precision time data, and achieve synchronization between different sensors. First of all, we need to select the time segment, the time length is T_n, and divide the fusion time of the time segment according to the different motion states of the target. The time segment corresponding to the high-speed motion is in seconds, the time segment corresponding to the motion is in minutes, and the

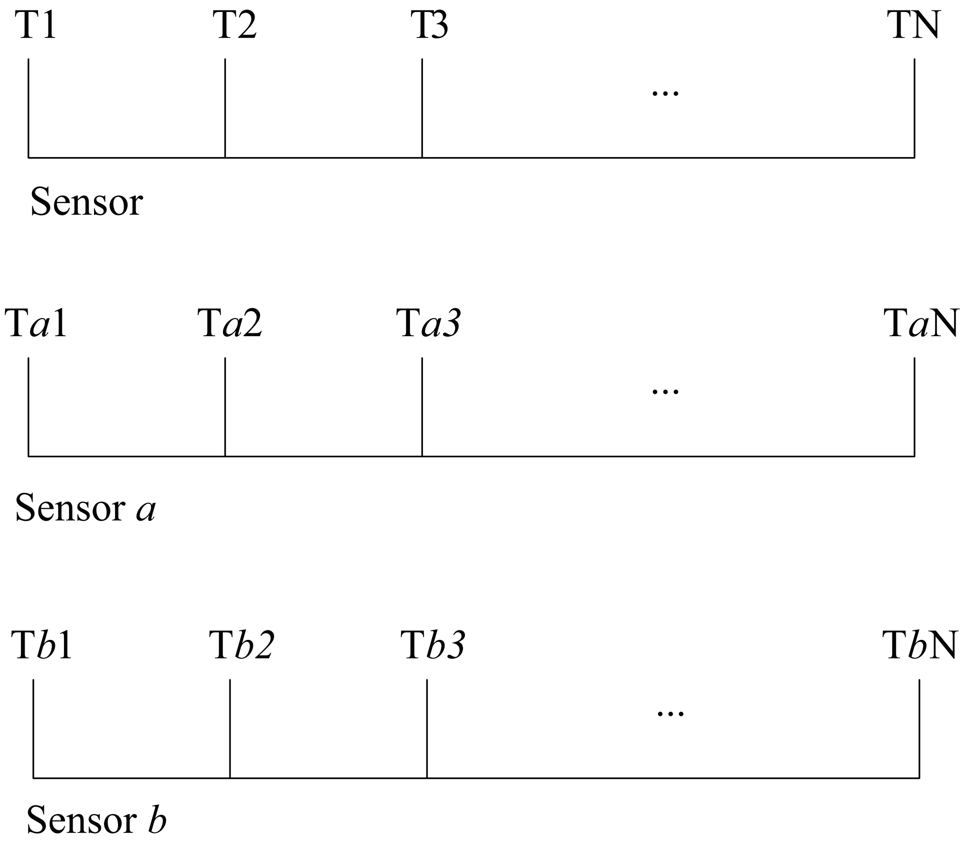

Figure 2 Measurement distributions of different sensors in the same time segment

corresponding time segment corresponding to the target is in hours. Secondly, the measurement data obtained by different types of sensors are sequenced incrementally according to the accuracy of the sensors. Finally, the synchronization of a high-precision time segment with a low-precision time segment is achieved by interpolation and extrapolation. Assume that the measurement data distribution in the same time slice of the sensor is:

In the above figure, sensor *a* represents the high-precision measurement data, and sensor *b* represents the low-precision measurement data. This process can be regarded as approximately linear, which is expressed as:

$$x = \frac{s}{k - k_i}(m/i) \tag{1}$$

In formula (1), x represents approximation function, k and k_i represent measurement data, s represents measurement time, m/i represents multi-source information registration parameter.

2.2 Conflict Measurement of Multi-Source Information Fusion

Taking the knowledge of experts in different fields as multiple evidence sources for the system [9–12], for the problems of imprecision, incompleteness and uncertainty in multiple evidence sources, using D-3 evidence theory for evidence fusion has the advantages of producing reliable fusion results and good scalability. Based on the traditional multi-source information fusion system that uses D-3 evidence theory, the conflict measurement is added, which makes the new fusion system not only retain the advantages of the traditional system, but is also more adequate for the weight coefficient distribution of the conflict evidence:

2.2.1 Multi Source Information Conflict Measurement Standard Setting

For multiple evidences, this paper uses the method of conflict consistency to measure the degree of conflict among evidences. It is found that the average degree of conflict between two evidences is more acceptable than the global conflict degree. Therefore, the average conflict degree and consistency degree between two evidences are used to express the consistency and conflict degree. The degree of conflict between evidences can be obtained by calculating the trust value assigned to the empty set. Therefore, the degree of conflict between two evidences can be expressed by the conflict matrix. Assuming that there are a total of l evidences, the conflict size of evidence i and j is k, that is, the conflict matrix is:

$$k = \begin{bmatrix} 0 & k_{12} & k_{1l} \\ k_{21} & 0 & k_{2l} \\ \vdots & \vdots & \vdots \\ k_{l1} & k_{l2} & 0 \end{bmatrix} \tag{2}$$

Since the conflicts of evidence i and j are equal to those of evidence j and i, the conflict matrix k is a symmetric matrix. There is no conflict in the single evidence itself' so the elements on the diagonal of the conflict matrix are all 0.

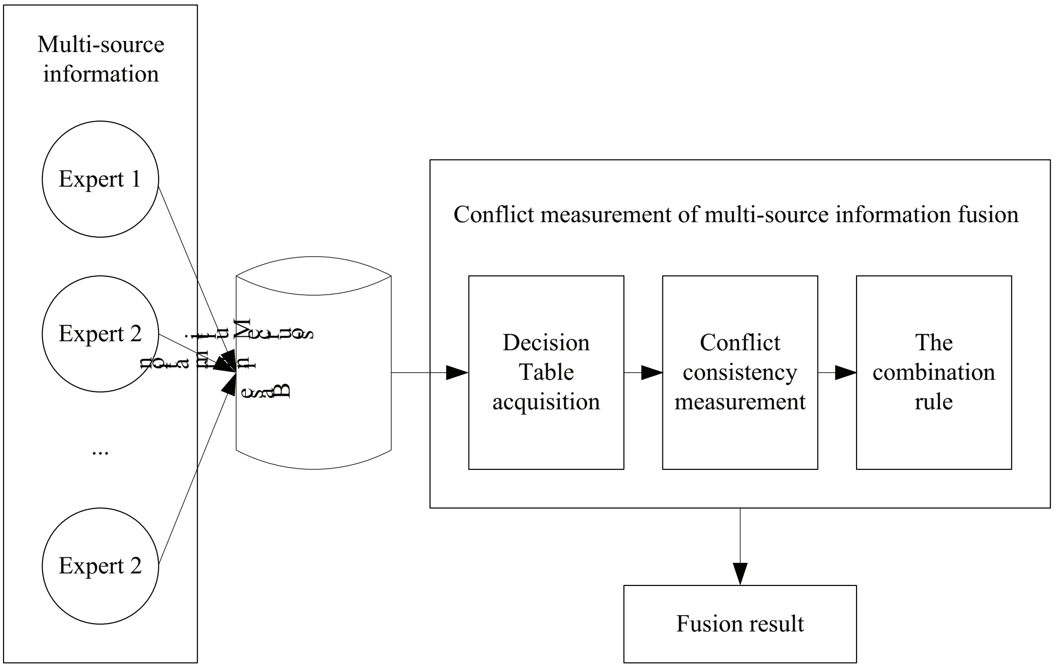

Figure 3 Conflict measurement framework of multi-source information fusion

Through the conflict matrix, we can obtain the average degree of conflict between evidence i and other $(l-1)$ evidences is $k_i = \frac{1}{l-1}\sum_{j=1} a$. The consistency of evidence refers to the degree of consistency between two evidences, that is, the sum of the product of the same proposition credibility between evidences. We can obtain the consistency

$$c = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1l} \\ c_{21} & 1 & \cdots & c_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ c_{l1} & c_{l2} & \cdots & 1 \end{bmatrix} \tag{3}$$

The average consistency between evidence i and other $(l-1)$ evidences is obtained by the above formula.

Only by setting a adequate conflict measurement standard can we know the degree of conflict among the evidence. Therefore, the idea of group decision-making is introduced: when multiple experts make decisions, when their consensus is more than their divergent views, in order to enable them to reach consensus, some differences between them must be discounted so that their views are basically the same. The intensity of conflict in the evidence is measured by the difference of consistency and conflict between evidences. The expression is:

$$cm(i) = \frac{a}{k_1 + d} \tag{4}$$

In formula (4), $cm\ (i)$ stands for the conflict intensity of evidence, k_1 stands for the conflict measurement parameter, d stands for the conflict degree, and a stands for the multi-source information parameter. When $cm\ (i) > 1$, there is conflict in the evidence, the greater the value of $cm\ (i)$ is, the more serious the conflict is; when $cm\ (i) = 1$, there is complete conflict between evidence i and other $(l-1)$ evidences, and when cm $(i) = 0$, there is no conflict between them.

2.2.2 Determination of Conflict Rules in Multi-Source Information Fusion

The multi-source and multi-modal data in the sensor are directly fused at the data level to complete data registration [13-17], feature extraction, data association and state estimation, and feature level fusion. Finally, the decision level fusion is completed based on the database and knowledge base, creating decision instructions, uniformly executing and feedback sensor management, forming a closed-loop. Based on this, the multi-source information fusion model of the Internet of things is divided into four stages: perception, association, decision-making and action, as shown in the following figure:

In this closed-loop fusion process, after data preprocessing, spatiotemporal matching and data level fusion, the central server is responsible for feature level fusion, feature extraction and scenario correlation; this is the correlation stage in the model. In the decision-making stage, based on the overall impression formed by each association, situation estimation and function evaluation are carried out to make decisions. The association stage and decision-making process are closely combined in the intelligent processing system. In the action phase, through the real-time evaluation and feedback of the sensor and the whole fusion process, the adaptive information acquisition and processing process as well as the optimal allocation of resources are realized, so as to achieve the closed-loop control.

When choosing combination rules or improving existing rules according to principle standards, we should not only retain the nature and advantages of traditional DST, but also solve the problem of conflicting evidence. Therefore, the exchange law, one of the basic properties of traditional DST, is taken as the principle standard, the expression of which is:

$$m_1 \oplus m_2 = m_2 \otimes m_1 \tag{5}$$

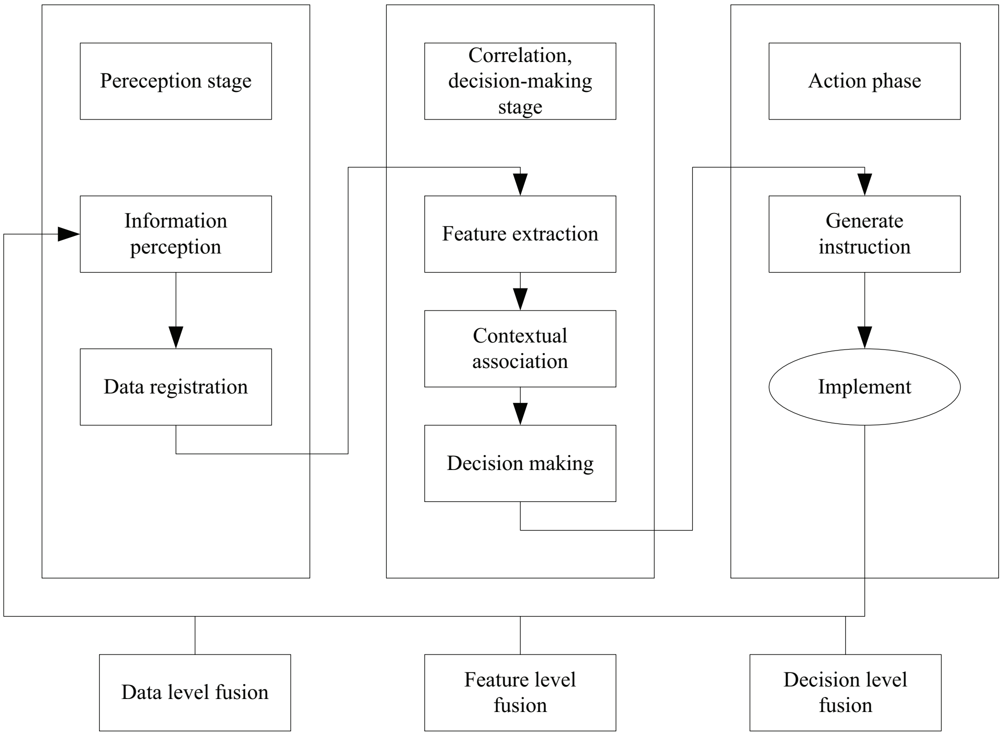

Figure 4 Information fusion process

In formula (5), m_1 and m_2 respectively represent the parameters of multi evidence combination. According to this principle, the order of evidences does not affect the synthesis results.

Hence, to determine the weight of evidence, and in order to ensure that multiple evidences reach a consensus, we must discount the differences between them. Therefore, according to the conflict consistency, we can objectively and fairly assign different weights to the evidence with low credibility, and place full trust in the consistent evidence, that is, whose weight coefficient is 1. For l evidences, the weight coefficient is determined:

1) Given two sets θ_1 and θ_2, the initial set is empty;
2) According to the conflict matrix and the consistent matrix, the average conflict degree k_i and the average consistent degree c_i are calculated respectively, and the size of $CM\ (i)$ is obtained;
3) When $cm\ (i) > 1$, evidence i is assigned to set θ_1; when $cm\ (i) < 1$, evidence i is assigned to set θ_2;
4) Repeat the above steps until all evidences are allocated to the set;
5) For the set θ_2, the weight given to the set element is 1;
6) For the set θ_1, the average conflict degree is normalized.

After the above discounting operation on the evidence source, the evidence with various levels of reliability plays different roles in the conclusion, and its weight coefficient in the combination rule also changes correspondingly, but there are still conflicts among multiple evidences. Whether there is available information in the conflict between evidences and how to allocate the available information reasonably are the problems that need to be resolved at present. In fact, when we deal with objections in group decision-making, we will not completely deny their value; rather, they are treated as reservations, in the belief that objections will give rise to useful information. Therefore, according to the idea of group decision-making, if we discard the conflict information completely in the combination rules. We will not only lose any useful information arising from the conflicting evidence, but also we may be led to conclude that the combination result is inconsistent with common sense. Therefore, a combination rule based on conflict information is proposed

$$c = \frac{a}{l * (m-1)} \sum i \tag{6}$$

In formula (6), c represents the average conflict degree, l represents the combination rule parameter, $m - 1$ represents the average support degree of multi-source information, a represents the credibility of evidence, and $\sum i$ represents the average support degree of information.

In the conflict processing of multi-sensor information fusion, target tracking is the bottom key part of the conflict processing of information fusion, and it is the basis of the conflict processing of other levels of the system. Data association is the core technology in the fusion conflict processing, and also the key content of information fusion technology Due to the influence of noise, the complexity of the target environment, electromagnetic interference, false measurement, sensor's own characteristics and so on, the target tracking technology is facing a huge challenge. Adequate processing of the relationship between measurement information and target source is the key to solving the problem of target-tracking technology And data-association technology is used to determine whether the measurement comes from the target

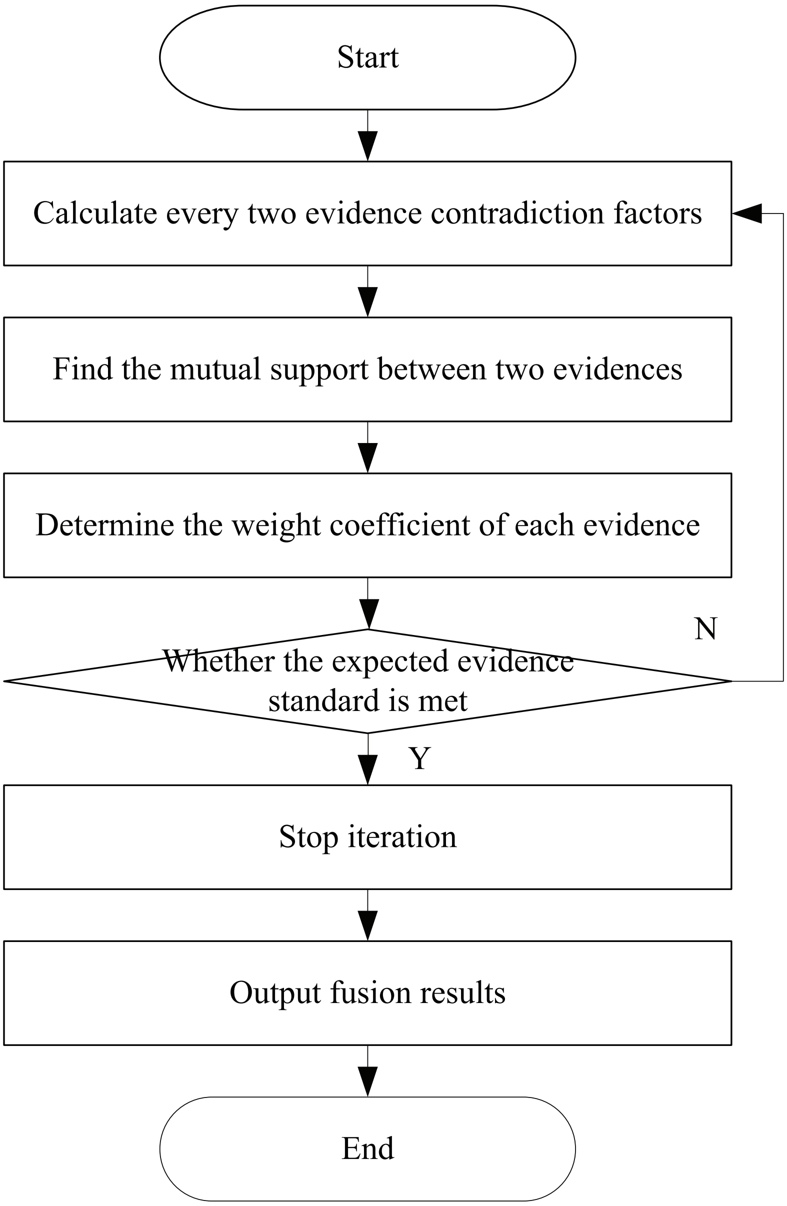

Figure 5 Information normalization process

according to the measurement information received by the sensor process of standard source. The performance of the target tracking algorithm depends on the association result. When the association result is correct, the target can be effectively tracked. If the target deviation is too large, it is often caused by the association result error. When an association error persists, the target may even be lost. In a multi-clutter and multi-target environment, there are too many measurements in the tracking gate, and the tracking gates between different targets will be too close or may even overlap, which makes the data association more difficult. An efficient algorithm for data association plays an important role in solving the problem of target tracking. The problem of data association acts on each link of the target tracking, which can be divided into three parts:

(1) data association of "measurement";

(2) data association of "measuring track";

(3) "track data association".

Among them, "measurement" data association is the process of initializing the track information of new targets; "measuring track" data association is the process of updating track and maintaining track; "track data association" is the process of determining the subordination relationship between local track and tracking target. Data association of the measured track is the key content of this chapter. Before data association processing, information normalization is needed to fu rther improve the accuracy of state and identity estimation, a battlefield situation or threat. In order to ensure that the expected evidence obtained meets the basic confidence value and the condition of 1, the weight vector of evidence should be normalized. The algorithm flow is:

For sensor information which seriously conflicts with most other information due to the influence of uncertain factors, the circular wave gate method is used to measure whether it originates from the decision threshold of the target. The circular wave gate is used mainly for the initial part of the track, which is generally used as the initial wave gate. It

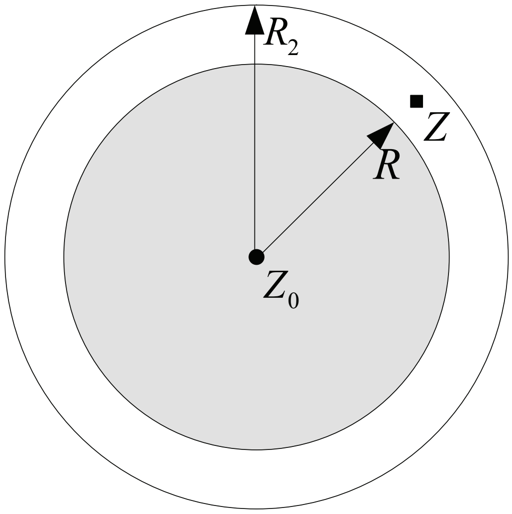

Figure 6 Annular gate

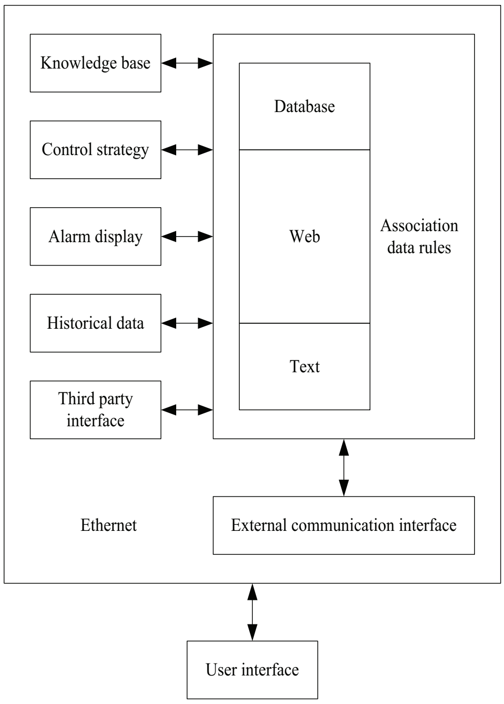

Figure 7 Experimental data processing flow

is based on the arrow of the track to establish a minimum, maximum movement speed and sampling room of the target. The basic form of 360° annular wave gate is:

The white area in the figure represents the effective area of the tracking gate, where Z_0 is the prediction center of the track and Z is the measurement value in the tracking gate. After processing with this method, it will effectively reduce its weight and position in information fusion, so that multi-source information can still obtain a more adequate fusion result after DS rule fusion, so as to complete the processing of multi-source information fusion conflict.

3. EXPERIMENTAL COMPARISONS

Experiments were conducted to verify the effectiveness of the designed multi-source information fusion conflict processing algorithm under the Internet of things. In order to ensure the rigor of the experiment, the traditional algorithm was compared with the proposed algorithm, in terms of the processing time required for multi-source information fusion conflict.

3.1 Establishment of Experimental Platform

The experimental platform designed in this paper displays the real-time status, analysis processing and statistical level display of the conflict processing of multi-source information fusion of the two algorithms, and finally presents them through the graphical interface to facilitate human-computer interaction. The information collected in real time is extracted and integrated by a heterogeneous database system, and the data structure is unified. Through the fuzzy inference information fusion program, the association rules of various

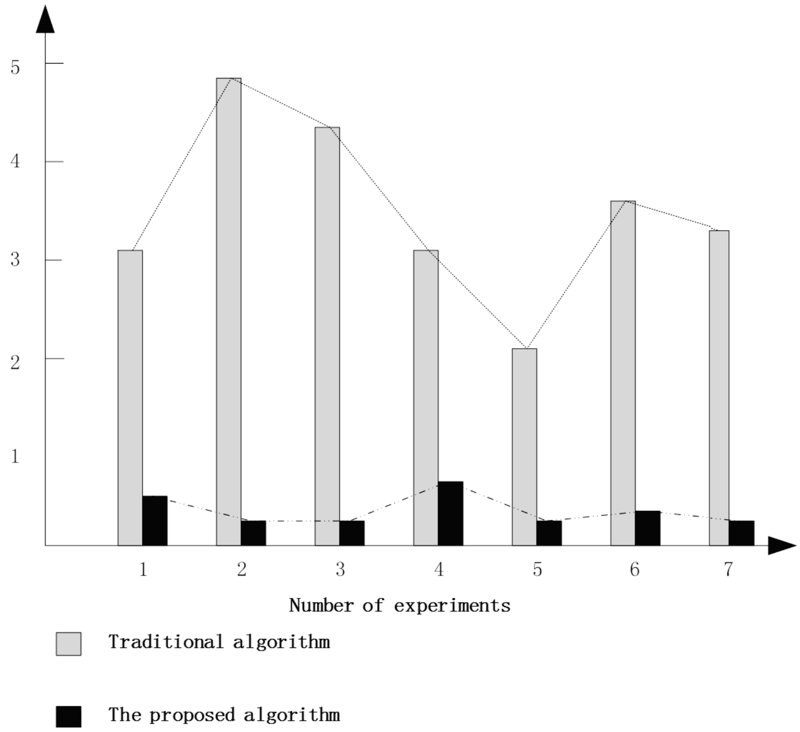

Figure 8 Comparison of experimental results

information and monitoring results obtained by the algorithm and the real-time environment information after the unified data structure are taken as input, and the multi-source information fusion conflict processing results of the two algorithms are calculated.

The MatLab tool is used for the processing and analysis of filzzy reasoning information fusion. The software has a large reliable and stable algorithm library and powerful scientific calculation function, and is widely used. Almost all engineering calculation fields provide an efcient and accurate toolbox.

3.2 Analysis of Experimental Results

The experimental results of the traditional algorithm and the proposed multi-source information fusion conflict processing algorithm under the Internet of things are given below

The analysis of the above experimental results shows that the processing time of the traditional algorithm is more than the conflict processing time of the design method, and the difference between the second and the third times is the largest. Therefore, the experiments have proven that the proposed new algorithm can effectively and more quickly resolve the conflict of multi-source information fusion, which is of practical significance.

4. CONCLUSIONS

As a new technology of interdisciplinary fusion, multi-sensor information fusion technology can synthesize multi-source information, eliminate redundant and contradictory items from multi-source information, and improve the accuracy of the system. The main aim of this research was to address the problem of the long processing time of the traditional multi-source information and conflict processing algorithm, and to design a multi-source information and conflict processing algorithm under the Internet of things. Our research algorithm comprises two innovations. Firstly, data association technology is the core part of multi-sensor information fusion technology, which is directly related to the quality of fusion results. The data association algorithm and joint data association algorithm are analyzed and studied in detail, and the idea of evidence theory is introduced to improve the two algorithms. The multi-sensor measurement information and the associated estimation information are used as two sets of evidence for fusion calculation, the weight value of the target is obtained, and the estimated value is fused according to the corresponding fusion equation. Secondly, the measurement information received by the sensor is processed using the idea of evidence theory to allocate the weight, and data fusion of the obtained information, which is the main content of this study. However, there are still several issues that need to be addressed in depth, requiring further research. To date, no unified framework has been proposed by any researcher for the establishment of multi-sensor information fusion model; most of the current models are based on a specific actual situation requiring specific analysis. The establishment of an adequate multi-sensor fusion model is a problem that needs further study Moreover, in regard to data association, the setting of a system state model affects the estimation results. The state model plays a decisive role in one-step prediction results, and if the deviation between the actual measurement results and the one-step prediction results is too large, it will affect the tracking accuracy of the target to a certain extent. It is difficult to update the state model in real time according to the actual situation of the target. Further research is needed to obtain better results for multi-source information fusion conflict processing.

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