High-Discrimination Multi-sensor Information Decision Algorithm Based on Distance Vector

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Abstract. In the process of sensor target recognition, attitude estimation and information decision-making, most of the current sensor information decisions require probability conversion or weight calculation of sensor data. The calculation process is complex and requires a large amount of computation. In addition, the decision result is greatly affected by the probability value. This paper proposes a multi-sensor information decision algorithm with high-discrimination based on distance vectors. At the same time, the support function, dominance function and discrimination function for the algorithm are presented. The dominance function is obtained through the normalization processing of the support matrix, and then the dominance function after normalization is sorted. The maximum value is taken as the optimal solution. The discrimination function mainly provides the basis for the evaluation of the algorithm. The simulation results show that the discrimination degree of this method in sensor information decision-making reaches more than 0.5, and the decision-making effect is good. Compared with the classic D-S evidence theory, this algorithm can effectively avoid the phenomenon that D-S evidence theory contradicts with the actual situation when making a decision. It is less affected by a single sensor and the decision result is stable. Compared with the probabilistic transformation of the initial data of the sensor in the decision-making process, it has obvious advantages.

Keywords: Information decision · Distance vector · Support matrix · Dominance function · Discrimination function

1 Introduction

The rapid development of artificial intelligence, big data and 5G technologies has accelerated the process of "Internet of Everything" [1]. As an important medium for the machine to perceive the world [2], the sensor network directly affects the development and progress of society [3] because of its security, intelligence and advanced nature. An integrated sensor network (WSN) is usually composed of multiple sensor nodes, these sensor nodes seem to be independent. In fact, due to the correlation of the monitoring

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range, method and object, there is a potential internal connection between each data [4]. Using this internal connection, a relatively correct result is automatically determined by the algorithm, which makes a reference for people's scientific research [5].

Ref. [6] combined support vector machine (SVM) and improved D-S evidence theory to propose multi-classifier information fusion. Analysis shows that this method can effectively fuse classifier information from different SVM, it has strong robustness and high accuracy. Ref. [7] proposed a new divergence measure for the confidence function for the high-conflict problem of D-S evidence theory to measure the difference between the basic probability distributions in D-S evidence theory. Analysis shows that this method provides a promising solution for measuring the difference between belief functions in evidence theory. Aiming at the problem that the conflict weight of D-S evidence theory cannot be effectively reduced, Ref. [8] improved the D-S evidence theory and introduced a combination rule, which effectively reduced the conflict weight assigned by the basic probability allocation ordering. Ref. [9] proposed a trust model to improve D-S evidence theory. This model defines the evidence variance according to the Jousselme distance, modifies the evidence before the fusion, and then conducts the fusion through D-S evidence rules. The simulation results show that the model can accurately find the malicious nodes in the sensor network, which is conducive to improving the security and robustness of the network. Ref. [10] proposes a comprehensive information fusion method based on evidence theory and group decision-making. The weight of combination and disjunction rules are adjusted according to the consistency function of focus elements. Simulation result shows that this method can obtain reasonable and reliable decision results. Ref. [11] proposes an improved strategy of evidence theory based on confidence to solve the conflict problem of D-S evidence theory. The algorithm extracts weight from the preliminary predicted values of four neural networks, constructs BPAs function reasonably, and verifies the application effect of the system through examples. Ref. [12] proposed a similar Jaccard coefficient matrix partitioning processing method, which corrected the evidence source by calculating the weight of each sensor node, this method effectively solved the high conflict problem existing in D-S evidence theory, and reduced the decision-making risk. Ref. [13] proposed a multi-source information fusion fault diagnosis method based on D-S evidence theory. This method uses fuzzy subjection functions to construct the basic probability assignment of three evidence bodies. At the same time, in order to solve the conflict problem of D-S evidence theory, a D-S evidence theory based on the similar distance of new evidence is proposed. The analysis shows that the fault diagnosis results can be improved effectively. According to the conflict of D-S evidence theory. Ref. [14] proposes a testability evaluation method based on improved D-S evidence theory, establishes the density distribution function of equipment testability fault index detection rate, and constructs the quality function. At the same time, Lance and Williams distance are introduced to improve the information fusion of D-S evidence theory. The test results showed that this method had a good evaluation effect. Ref. [15] uses rough set theory and cloud parameter calculation, and combines D-S evidence theory to fuse multi-source information and identify faults. Simulation results show that this method can accurately identify faults; Ref. [16] makes use of the proximity of evidence in the process of sensor information decision-making, and keeps important information. At the same time, the conflict problem of D-S evidence theory is the weighting processing. Simulation analysis shows that this method can reduce the impact of conflict and improve the decision accuracy. The above methods have achieved good results in the process of sensor information decision-making, but the calculation process is relatively complex, most of the algorithms need to assign probability to the data collected by sensors, and seldom consider the characteristics and evaluation criteria of sensors.

In this paper, we make full use of the evaluation grade range of sensor data in the monitoring system, combine with the actual measured values, and calculate the support degree among the sensor data by using the distance between the actual values and the standard values, and finally get the system decision result. The main content and structure of the contents are organized and shown below. In Sect. 2 to 4, the fusion level, fusion process and decision model are reviewed. In Sect. 5 and 6, a more detailed description of proposed algorithms are given based on the distance vector. The performance analysis and discussion are described in Sect. 7 and concluded in the Sect. 8.

2 Multi-sensor Information Fusion Level

Multi-sensor information fusion includes research on transmission protocol and sensor network node information fusion, both of which are used to solve the redundancy problem of information acquisition in multi-sensor system, so as to improve the accuracy of information acquisition and reduce the amount of data sent by nodes. Figure 1 is a functional model of multi-sensor information fusion [17], whose fusion process can be divided into multiple levels. Firstly, the source data collected by the sensor is preprocessed. Secondly, the fusion results are obtained by further processing according to the application field. The technologies involved in fusion include data association, target tracking and identification, situation estimation, impact assessment and process assessment, among which the higher-level fusion technologies all involve information decision-making.

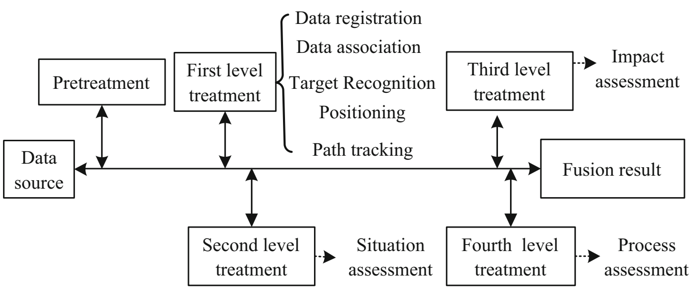

Fig. 1. Multi-sensor information fusion function model

3 Multi-sensor Information Fusion Process

Figure 2 shows the basic fusion process of multi sensor information [18], and the fusion process of data, features and decision-making is given in Fig. 2. First, the data collected by the sensor is preprocessed, including signal rectification, filtering and amplification. The first level of fusion directly sends the preprocessed data to the fusion center to obtain the fusion result. In the second level of fusion, the preprocessed data are extracted for features and sent to the fusion center to get the fusion results. This level of fusion is usually applied to data association and target recognition. The third level of fusion is to add the preliminary decision based on the second level of fusion, and then send the decision results to the fusion center to get the output results. This level of information fusion is often used in the field of information decision-making, which belongs to a higher level of information fusion, and the difficulty is increased to a certain extent compared with the first two levels of fusion.

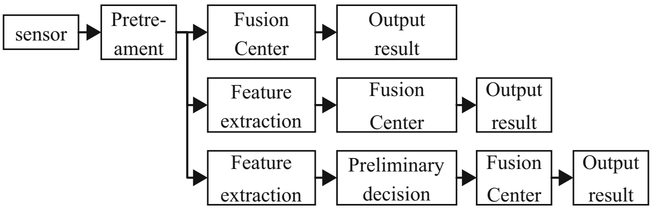

Fig. 2. Basic fusion process

4 Multi-sensor Information Decision Model

Figure 3 is a multi-sensor information decision model. There are n decision criteria and m sensor nodes. First, the measurable range of each sensor is divided into several intervals, and the central measurement value of each interval is taken as an evaluation standard (abbreviated as ICV) which is placed into N decision criteria corresponding to the sensor respectively. Second, the distance difference between the actual value of the data collected by the sensor node and its corresponding evaluation standard needs to be obtained, which can be named support matrix. That is, the support of each actual measured value relative to the node standard. Third, the support function is obtained by summing the distance difference between the actual measured value of each sensor and its n evaluation criteria. Finally, the data processing algorithm is used to get the superiority of each group's decision results, and the maximum value is taken as output result of the decision.

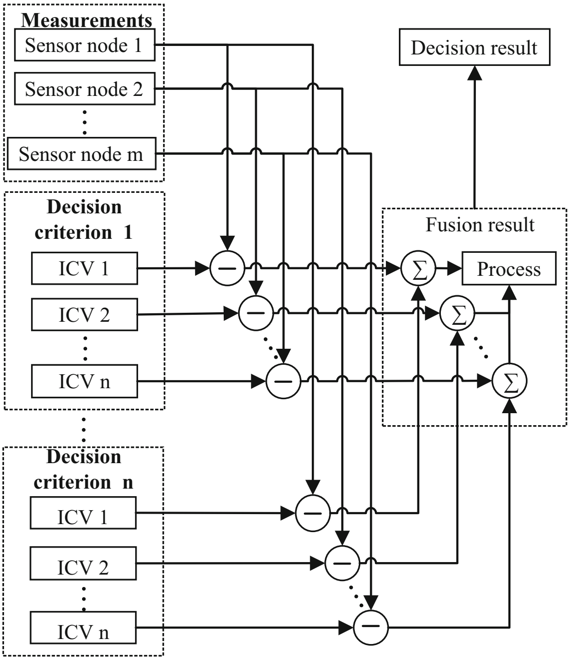

Fig. 3. Multi-sensor information decision model

5 Algorithm Implementation Principle

5.1 Single Attribute Information Fusion Algorithm

Figure 4 is a schematic diagram of single attribute sensor information decision. Assuming that the same kind of sensors are used for measurement in a monitoring system, there are four evaluation levels in the system, the value range of the first evaluation level is $a_1 \pm \Delta t$, and the value ranges of the other three evaluation levels are shown in Fig. 4. Let b be the actual measured value of the sensor, calculate the absolute value of the distance between b and the center value of each value range, and take the evaluation level range where the minimum absolute value is located as the final decision result. As shown in Fig. 4, is decision result 2 (abbreviated as DR2).

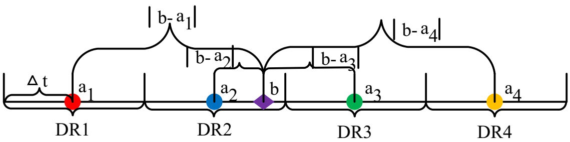

Fig. 4. Single attribute information decision schematic diagram

5.2 Multi-attribute Information Fusion Algorithm

Generally, when using sensor information to make decisions, it is necessary to perform probability conversion on the data collected by the sensor, and then make decisions through relevant algorithms. However, when using sensor information to make decisions, the decision criteria will be given. Figure 5 is a standard diagram of information decision value, and a_1^1 means that under this standard, the value range of sensor 2 is $a_1^1 + \Delta t$.

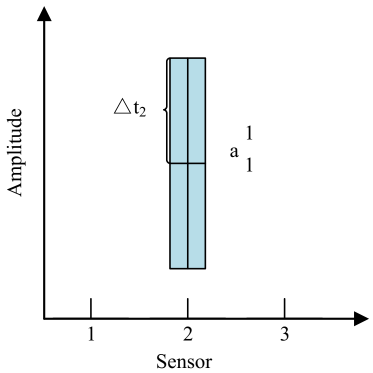

Fig. 5. Decision value criterion

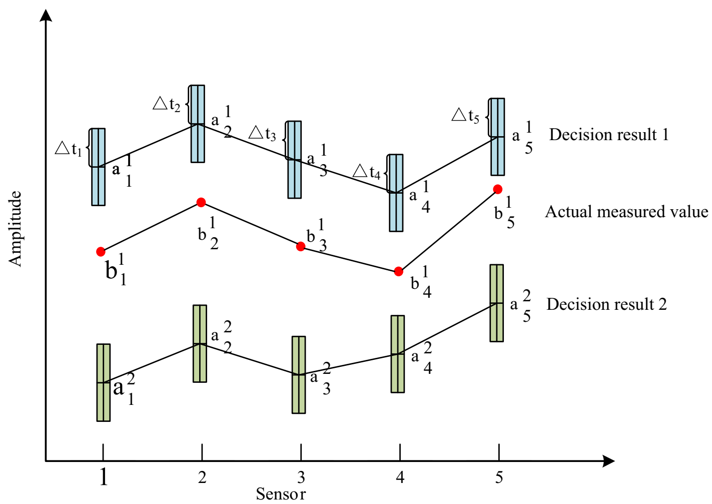

Fig. 6. Multi-attribute information decision principle diagram

The principle of multi-attribute information decision-making is shown in Fig. 6. Where $a_1^1, a_2^1, \cdots a_5^1$ are the central value of the value range for each sensor corresponding to DR1. Similarly, and $a_1^2, a_2^2, \cdots, a_5^2$ are the central value of the value range for each sensor corresponding to DR2, and $b_1^1, b_2^1, \cdots, b_5^1$ are the actual measured values of the first group. Next, the single attribute decision making method is extended horizontally to multi-attribute information decision making, and the distance vector modulus of the actual measured value and the central value of the standard decision range is vertically calculated, and the sum of the distance vector modulus of each decision result is calculated horizontally. The smaller the value is, the closer the calculation result is to the decision result.

6 Multi-sensor Decision Algorithm Based on Distance Vector

The specific process of the multi-sensor decision algorithm based on distance vector is described as below.

Step 1. If there are n evaluation levels and m sensors in the evaluation system, the value range of the $i-th$ sensor corresponding to each level j is $a_i^j \pm \Delta t_i$, where a_i^j is the center value, then the level j can be vector as $G_{\mathrm{j}} = \left(a_1^j, a_2^j, \cdots, a_m^j\right)$.

Step 2. Suppose the maximum value of each sensor is $max(a_i)$ and the minimum value $min(a_i)$, the actual measured value is a vector as $B = (b_1, b_2, \cdots, b_m)$, 且 $min(a_i) \le b_i \le max(a_i)$.

Step 3. Let N_j be the support degree of j to the measured values of each sensor, $\Phi_{ji} = \left(A_j, A_i\right) = b_i - a_i^j$ represents the distance from the measured value b_i to the evaluation a_i^j, where $i \le m, j \le n$.

Then the support matrix can be expressed as follow,

$$N\left(A_i, A_j\right) = \begin{pmatrix} \Phi(A_1, A_1) & \Phi(A_1, A_2) & \cdots & \Phi(A_1, A_m) \\ \Phi(A_2, A_1) & \Phi(A_2, A_2) & \cdots & \Phi(A_2, A_m) \\ \vdots & \vdots & \cdots & \vdots \\ \Phi(A_n, A_1) & \Phi(A_n, A_2) & \cdots & \Phi(A_n, A_m) \end{pmatrix} \tag{1}$$

The support function is obtained from the above Eq. (1) as follow,

$$\delta(A_i) = \sum\nolimits_{i=1}^{m} \Phi\left(A_j, A_m\right) \tag{2}$$

Step 4. Normalization processing,

$$T_j' = \frac{\delta\left(A_j\right)}{\delta} \tag{3}$$

where $\delta = \sum_{j=1}^{n} \delta\left(A_j\right),\ T' \in [0, 1]$.
then the result of the dominance function is,

$$T_i = 1 - T_j' \tag{4}$$

Step 5. According to the calculation scheme of Definition 1–4, the normalized function $s(A_i)$ is:

$$S_j = \frac{T_j - \underset{j \le n}{min}\left\{T_j\right\}}{\underset{j \le n}{max}\left\{T_j\right\} - \underset{j \le n}{min}\left\{T_j\right\}} \tag{5}$$

Sort the calculation results in S_j, and take $max\{S_j\}$ as the optimal solution, that is, $S_j = 1$.

Step 6. Let φ be the discrimination function, then,

$$\varphi = max\{\varphi_j\} = \max_{j \le n}\{S_j\} - S_j \tag{6}$$

Step 7. When m = 1, $\delta(A_j) = \Phi(A_j, A_1)$, then, $T_j = 1 - \frac{\delta(A_j)}{\sum_{j=1}^{n} \delta(A_j)}$, the optimal solution scheme can be solved by Eq. (5).

7 Simulation and Analysis

Example 1. Assume that the temperature of a certain water area is to be graded, and the evaluation criteria are shown in Table 1. It is tested with a temperature sensor, and the temperature of current water is set to 15 °C.

Table 1. Temperature evaluation standard

Level	First level	Second level	Third level	Fourth level
Temperature range	30–35 °C	20–30 °C	10–20 °C	−5–10 °C

The calculation results of the normalized function in Table 2 can be obtained from Table 1, where DDV represents the distance difference between the measured value and the center value.

Table 2. The result is calculated by the normalized function

Level	First level	Second level	Third level	Fourth level
Temperature range	30–35 °C	20–30 °C	10–20 °C	−5–10 °C
Central value	32.5 °C	25 °C	15 °C	2.5 °C
DDV	17.5 °C	10 °C	0 °C	12.5 °C
T_j	0.5625	0.75	1	0.6875
S_j	0	0.4286	1	0.2857

Then sort the calculation results of S_j, and take $max\{S_j\}$ as the optimal solution, that is, the water area has three levels. The calculation results show that the water area is of third level. According to Eq. (6), the discrimination degree is 0.5714.

Example 2. It is assumed that a comprehensive evaluation of the pollution of a certain water area is required. The evaluation criteria are shown in Table 3. The environmental

Table 3. Evaluation criteria for water pollution

Level	Temperature	pH	Turbidity	Conductivity
First level	30–35 °C	9–10	35–40%	0.8–1
Second level	20–30 °C	8–9	25–35%	0.5–0.8
Third level	10–20 °C	6–8	10–25%	0.3–0.5
Fourth level	−5–10 °C	4–6	0–10%	0.1–0.3

parameters of water quality that collected by sensor nodes including temperature, pH, turbidity, conductivity, etc. and the actual measurement results are 12 °C, 7.5, 20%, and 0.4 respectively.

The following vector expressions are obtained from Table 3,

$$G_1 = (32.5, 9.5, 37.5, 0.9)$$

$$G_2 = (25, 8.5, 30, 0.65)$$

$$G_3 = (15, 7, 17.5, 0.4)$$

$$G_4 = (2.5, 5, 5, 0.2)$$

Then get the support matrix as,

$$N\left(A_i, A_j\right) = \begin{pmatrix} 20.5 & 2 & 17.5 & 0.5 \\ 13 & 1 & 10 & 0.25 \\ 3 & 0.5 & 2.5 & 0.2 \end{pmatrix}$$

According to Eqs. (1), (2) and (3), the following results can be obtained,

$$T_1 = 0.5865,\ T_2 = 0.7507,\ T_3 = 0.9388,\ T_4 = 0.7223$$

and according to Eqs. (4), the following results can be obtained,

$$S_1 = 0,\ S_2 = 0.4661,\ S_3 = 1,\ S_4 = 0.3555$$

First, sort the calculation results of S_j, and then take $max\left\{S_j\right\}$ as the optimal solution. The results show that the water area meets the third-level standard and are consistent with common sense.

Example 3. Suppose that a recognition framework is composed of A, B and C, and the evaluation criteria of the corresponding evidence are shown in Table 4. If the actual measured values of the sensors are 60, 38, 1.5 and 4.8 respectively, the basic probability distribution based on the measured values are shown in Table 5. In addition, the fusion results comparison of the proposed algorithm and D-S evidence theory as shown in Table 6.

Table 4. Evaluation criteria under the identification framework in Example 3

	A_1	A_2	A_3	A_4
A	90–100	0–15	0.5–0.8	3–5
B	75–90	15–30	0.8–1.3	1–3
C	50–75	30–50	1.3–1.8	−0.5–1

Table 5. Evidence data under the identification framework in Example 3

	$m(A_1)$	$m(A_2)$	$m(A_3)$	$m(A_4)$
A	0.1	0.1	0.1	0.9
B	0.3	0.32	0.45	0.1
C	0.6	0.58	0.45	0

Table 6. Comparison of fusion results of different methods

Method	m_1, m_2	m_1 , m_2, m_3	m_1 , m_2, m_3, m_4
D-S	$m(H_1) = 0.022$ $m(H_2) = 0.2115$ $m(H_3) = 0.7665$ $m(\theta) = 0$	$m(H_1) = 0$ $m(H_2) = 0.4515$ $m(H_3) = 0.7665$ $m(\theta) = 0$	$m(H_1) = 0.1724$ $m(H_2) = 0.8276$ $m(H_3) = 0$ $m(\theta) = 0$
Proposed method	$m(H_1) = 0$ $m(H_2) = 0.4508$ $m(H_3) = 1$ $m(\theta) = 0$	$m(H_1) = 0$ $m(H_2) = 0.4515$ $m(H_3) = 0.7665$ $m(\theta) = 0$	$m(H_1) = 0$ $m(H_2) = 0.2204$ $m(H_3) = 1$ $m(\theta) = 0$

It can be seen from the data in Table 6 that when the number of evidences is less than or equal to 3, each evidence shows that the recognition result is the most likely to be C, which is the same as the result of the method in this paper, and the recognition result is C. When the number of evidence is 4, the judgment result of D-S evidence theory is greatly affected by the basic probability distribution, which is contrary to the facts and has no reference value. However, the identification result of the method for proposed method is still C, which is consistent with common sense. The relationship between the recognition rate of C and the number of evidences in the two fusion methods are shown in Fig. 7. If the recognition rate of C is used to analyze the index, the recognition rate of this method is 1 when the number of evidence is 2, 3, and 4, while the recognition rate of D-S evidence rule is significantly lower when the number of evidence is 2, 3. And when the number of evidence is 4, the histogram of D-S evidence rule disappears, that is, the recognition rate is 0. The reason for analysis is that when the evidence is A_4, the basic probability assignment $m_4(A_4)$ appears a big conflict.

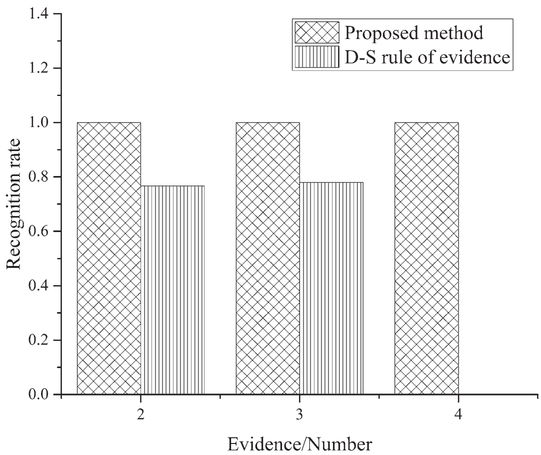

Fig. 7. Relationship between the recognition rate of C and the number of evidences

Furthermore, the degree of discrimination between the two methods is calculated separately, as shown in Table 7. The discrimination of the two methods is above 0.5, but when the number of evidence is 4, the discrimination of the method in this paper reaches 0.7796. However, the D-S evidence theory loses comparability due to the inconsistency between decision results and facts.

Table 7. Discrimination Comparison of different methods

Method	m_1, m_2	m_1, m_2, m_3	m_1, m_2, m_3, m_4
D-S	0.5550	0.5648	0.6552
Proposed	0.5592	0.5685	0.7796

8 Conclusion

This study proposes a multi-sensor information decision algorithm with high-discrimination based on distance vector, and the principle of the algorithm is analyzed from the perspective of single attribute and multi-attribute. The support matrix, dominance function and discrimination function of the algorithm can be used to obtain the optimal solution of the decision result and the evaluation basis of the algorithm performance. The analysis results show that the discrimination degree of the proposed method can reach more than 0.5, it can effectively avoid the conflict problem in the decision-making process compared with the traditional D-S evidence theory, and has obvious advantages over the application scenarios that need to assign the initial probability of the sensor in the decision-making process.

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