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Heterogeneous information fusion recognition method based on belief rule structure

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Abstract: To solve the problem that the existing situation awareness research focuses on multi-sensor data fusion, but the expert knowledge is not fully utilized, a heterogeneous information fusion recognition method based on belief rule structure is proposed. By defining the continuous probabilistic hesitation fuzzy linguistic term sets (CPHFLTS) and establishing CPHFLTS distance measure, the belief rule base of the relationship between feature space and category space is constructed through information integration, and the evidence reasoning of the input samples is carried out. The experimental results show that the proposed method can make full use of sensor data and expert knowledge for recognition. Compared with the other methods, the proposed method has a higher correct recognition rate under different noise levels.

Keywords: belief rule, heterogeneous information, intention recognition, hesitation fuzzy linguistic.

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1. Introduction

Information fusion system contains multilevel functional models, and target intention recognition is an important content of situation estimation [1]. According to the situation feature vector generated by situation awareness and combined with the military knowledge of field experts, battlefield deployment and action attempt can be judged [2]. In addition to the measured data obtained by various sensors, experts' knowledge of some target characteristics and attributes can also be obtained, and the two types of information are complementary [3]. Therefore, the fusion of sensor data and expert knowledge is of great practical significance.

The types of information sources can be divided into data-driven and knowledge-driven [4,5]. Data-driven mainly relies on learning and training data to acquire features. Training data are usually obtained by sensor measurement of targets, and these samples are used as training sets to train the model, so that it can classify unknown samples after training, including K-nearest neighbor (KNN), decision tree, and support vector machine. Knowledge-driven type is mainly based on the knowledge collected and sorted out from experts, sorting out a number of criteria to describe the relationship between features and categories, establishing a certain inference system, and then making inference decisions about the category of unknown samples [6]. Zhou et al. proposed that the initial rule base should be established on the basis of acquired expert knowledge, and then rules should be optimized through training data [7]. Tang et al. developed a knowledge-based Bayesian classifier to estimate conditional probability using training data [8]. Tang et al. establishd a fuzzy rule system based on expert knowledge, and then used training data to optimize the fuzzy membership function [9]. All the above methods first use expert knowledge to build the basic model, then use training data to optimize the model, and divide expert knowledge and training data into two different data sets. In the practical application of many information fusion systems, training data and expert knowledge exist at the same time but are not independent from each other. For example, for the problem of target intention identification, the characteristics of target individuals include the target distance, speed, heading and other attribute data measured by sensors. It also includes expert knowledge such as entity collaboration relationship and complexity of electromagnetic environment [10–12]. Obviously, the above method cannot be used to complete fusion processing under such conditions, and a new fusion recognition method needs to be found.

In order to integrate sensor data and expert knowledge organically to realize target intention recognition, a model that can effectively utilize these two kinds of infor-

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mation is needed. Rule is a common way to express knowledge and can be based on expert knowledge to build a rule-based system. Therefore, the rule-based modeling (RBM) approach has attracted more and more attention. The IF-THEN rule is a typical rule-based model, which can make full use of sensor data and expert knowledge information. Many fuzzy rule systems that use training data or expert knowledge to deal with classification problems have been proposed [13]. Belief function theory, also known as Dempster-Shafer theory [14,15], is a very powerful uncertainty modeling and reasoning framework first proposed by Dempster and later promoted by Shafer [16,17]. Yang et al. extended fuzzy rules under the framework of belief function theory and proposed belief rules [18], proposed a new knowledge expression, which has been applied in risk assessment, fault diagnosis and other fields. “Rule” in the structure of belief rules refers to production rules, which can be described as “IF-THEN” form. Belief rule structure can better explain and describe system mechanism. In this paper, sensor data and expert knowledge are fused through the structure based on belief rule to realize the effective recognition of target intention. Compared with the black box model such as deep neural networks (DNN), it has many advantages. First, it can effectively integrate quantitative information and qualitative knowledge. Second, reliable and understandable models can be established based on the structure of belief rules to enhance people’s cognition of the actual system [19].

The rest of the paper is organized as follows. In Section 2, the knowledge representation method is studied and the continuous probabilistic hesitation fuzzy semantic label is proposed to achieve accurate description of expert knowledge. In Section 3, the distance measure of continuous probabilistic hesitation fuzzy linguistic term sets (CPHFLTS) is studied from the perspective of the digital characteristics of random variables, the definition of tag efficiency value, expectation and variance is given, and the reliability calculation method of continuous interval semantic random variables is proposed. A fusion recognition method of heterogeneous information based on belief rule structure is proposed in Section 4. In Section 5, the proposed method is verified by combining the reliability value and the heterogeneous information fusion recognition experiment. Section 6 concludes this paper.

2. Knowledge representation and semantic labels

Semantic labels are an important knowledge representation method. Semantic representation is the core of semantic recognition and the basis of semantic computation and semantic output. In this section, the representation method of knowledge is given, and then the existing semantic representation methods are introduced. Finally, in order to overcome the problems existing in the existing semantic representation methods, the continuous probabilistic hesitation fuzzy linguistic term set is given, which can accurately describe more generalized semantic information.

2.1 Knowledge representation methods

In knowledge representation, knowledge is a concept, practice and process expressed in a structured way. Knowledge has relative correctness, indeterminacy and exploitability. Knowledge representation is to associate the knowledge factor in the knowledge carrier with knowledge so as to facilitate people to recognize and understand knowledge. Knowledge representation is a data structure that can be accepted by computers to describe knowledge. In order to make full use of expert knowledge to realize fusion recognition, the first problem is how to express expert knowledge correctly and reasonably. A series of rules of knowledge representation are stipulated in the knowledge representation method. In the field of artificial intelligence, the typical knowledge representation methods are symbolic method and vector method, which are essentially a kind of data structure and related information association. The symbolic method mainly includes first-order predicate logic representation, production rule representation, semantic network representation, and knowledge graph representation. The vector method is typically represented by distributed representation.

Production rule representation has become one of the most widely used knowledge representation methods in artificial intelligence. The production rule generally consists of instructions composed of conditions and actions, namely the so-called condition-activity rule (C-A rule), which can be written as C→A, i.e., “IF Condition THEN Action”. C is the available prerequisite, and A is the conclusion that should be obtained if C is true. As an important knowledge representation method, production rules can usually use semantic information to represent prerequisite knowledge.

2.2 Existing semantic representation methods

Language is the carrier of human thinking, and semantic information is the direct embodiment of the meaning contained in language. Semantic information is an important part of multi-source and heterogeneous uncertain information in decision-making level. As a kind of qualitative information, semantic information can better describe randomness and fuzziness in complex environment than numerical quantitative information. In 1975, Professor

Zadeh [20], the founder of fuzzy sets, proposed the concept of semantic computation and gave the mathematical description of semantic variables by machine computation. The semantic variable is a quintuple $(X, S(X), U, G, M)$, where X is the semantic variable name, U is the domain of semantic description value, $S(X)$ (denoted as S) represents the mapping from semantic to semantic description value s, G represents the rule that generates the semantic description value s, M is the semantic rule that reflects the meaning of the semantic description value s, and $M(s)$ is a fuzzy set in U. For the domain U, S can be regarded as the fuzzy division of U, which is a granularity representation of uncertainty. The ordered semantic label set can be used to describe the semantics of uncertainty, and the semantic label with granularity $g+1$ can be written as

$$S = \left\{ s_0, s_1, \cdots, s_g \,\middle|\, s_0 < s_1 <, \cdots, < s_g \right\} \tag{1}$$

where $g+1$ is the number of labels, g is usually an even number, and s_i is the ith ordered language label.

At present, semantic computing has been extended to many application fields and achieved many theoretical achievements [21]. Two pioneering achievements are the binary semantic representation model proposed by Spanish scholars Herrera and Martinez, and the concept of hesitant fuzzy linguistic term sets (HFLTS) proposed by Rodriguez et al. However, these two models also have limitations in practical application. They can only represent basic semantic information, but cannot do anything about more complex semantic information. In order to integrate expert knowledge more effectively in target intention recognition, more complex semantic information is often needed to represent expert knowledge. In this case, traditional semantic information representation methods cannot meet the requirements, so new semantic information representation methods need to be proposed.

2.3 CPHFLTS

Semantic recognition includes machine language representation, semantic computation and semantic output, and semantic representation and semantic computation are the key points. By analyzing the existing semantic representation methods, binary semantics has the limitation of single label semantic information description. Uncertain linguistic term sets (ULTS), HFLTS and probabilistic linguistic term sets (PLTS) cannot represent continuous semantics. Continuous interval-valued linguistic term sets (CIVLTS) lack consistency in describing the importance of semantic labels. This paper adopts a new semantic representation model which is named CPHFLTS. This semantic label can describe semantic information in a broader sense, and the use of continuous hesitation fuzzy semantics is helpful to adopt the opinions of multiple experts, because different experts may reach different conclusions for the determination of the same feature. Based on the definition of CPHFLTS, a distance measure suitable for CPHFLTS semantic computation is proposed. Combined with belief rule base (BRB) structure, a CPHFLTS-BRB model is formed for target intention recognition, which is successfully applied to the multi-attribute fusion intention recognition problem at the decision level.

Definition 1 S indicates the semantic label, $S = \{s_\alpha | \alpha = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$, then CPHFLTS is defined as

$$\tilde{H}_c(p) = \left\{ \tilde{h}_c^{(k)} | p^{(k)} | \tilde{h}_c^{(k)} \in \bar{S}, p^{(k)} \geqslant 0, k = 1, 2, \cdots, \left|\tilde{H}_c(p)\right|, \sum_{k=1}^{\left|\tilde{H}_c(p)\right|} p^{(k)} \leqslant 1 \right\} \tag{2}$$

where (k) represents the semantic label subscript, $\tilde{h}_c^{(k)} | p^{(k)}$ represents continuous semantic label $\tilde{h}_c^{(k)}$ with probability $p^{(k)}$, $\left|\tilde{H}_c(p)\right|$ is the number of continuous probability hesitation fuzzy semantic labels in $\tilde{H}_c(p)$, $\tilde{h}_c^{(k)}$ is a continuous interval semantic element.

$$\tilde{h}_c^{(k)} = [s_{(k)L}, s_{(k)U}],\ (k)L, (k)U \in [-\tau, \tau];\ (k)L \leqslant (k)U \tag{3}$$

Compared with binary semantic models, hesitant fuzzy semantic label sets, and probabilistic semantic label sets, etc., CPHFLTS can solve the problem that existing semantic representation methods cannot describe complex semantic styles such as continuous and probabilistic semantics. CPHFLTS can describe the semantic information of "the probability of being 30% larger than s_1 and smaller than s_3 is 0.4, the probability of being 20% larger than s_2 and 50% smaller than s_5 is 0.3", it can be expressed as $\{[s_{1.3}, s_3] | (0.4), [s_{2.2}, s_{4.5}] | (0.3)\}$. It can be seen that when the distribution probability $p^{(k)}$ is 1, CPHFLTS degenerates into a continuous semantic label set. When the continuous interval semantic element $\tilde{h}_c^{(k)}$ is a single semantic label, CPHFLTS degenerates into a probabilistic semantic label set. That is, CPHFLTS is a more generalized semantic label.

The schematic diagram of continuous probability hesitation fuzzy semantic label is shown in Fig. 1.

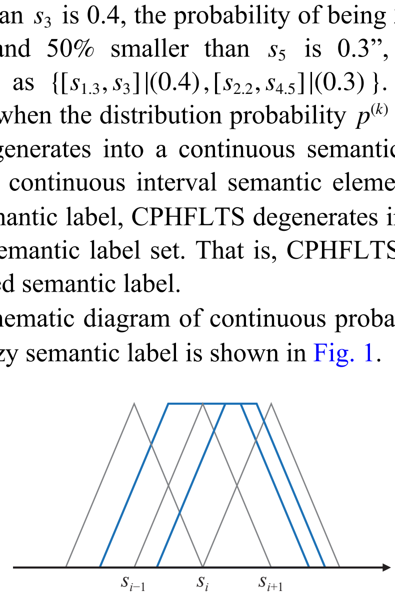

Fig. 1 Continuous probability hesitation fuzzy semantic label schematic

3. CPHFLTS distance measure

Achieving target intent identification requires categorization of patterns. This requires the similarity measure of the pattern to be recognized to describe the degree of similarity between the patterns. The distance measure is the basis of pattern recognition, so it is necessary to study the distance measure of CPHFLTS for target intention recognition based on continuous probabilistic hesitation fuzzy semantic label.

It can be seen that CPHFLTS, as an extension of hesitant fuzzy set, also has the problem of inconsistent number of semantic labels, but the traditional hesitant fuzzy set has no probability, so the new distance measure needs to solve the problem of probability superposition calculation.

This problem can be described as how to compute the distance measure between interval hesitant fuzzy sets for which there is a probability distribution. Through analysis, it is found that this problem is similar to the calculation of random variables under probability distribution, so this section defines the distance measure of CPHFLTS from the perspective of the numerical characteristics of random variables. First, the definitions of label efficacy value, expectation and variance of CPHFLTS are given. Then, the label efficacy value distance is given for two probabilistic label values of the same semantics, and the efficacy distance between semantic labels is defined on this basis. Finally, in order to integrate CPHFLTS with sensor data, the credibility definition of CPHFLTS is given.

Definition 2 $\tilde{H}_c$ is a continuum semantic random variable, and its possible value is a continuous interval $\tilde{h}_c^{(k)} = [s_{(k)L}, s_{(k)U}]$, the corresponding probability distribution is $P(\tilde{H}_c = \tilde{h}_c^{(k)}) = p^{(k)}$. The tag efficiency value, expectation and variance are defined as

$$\begin{cases} Q\left(\tilde{h}_c^{(k)}|(p^{(k)})\right) = \tilde{h}_c^{(k)} \cdot p^{(k)} \\ \mathrm{E}\left(\tilde{H}_c\right) = \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} Q\left(\tilde{h}_c^{(k)}|(p^{(k)})\right) \\ \mathrm{D}\left(\tilde{H}_c\right) = \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} \left[\tilde{h}_c^{(k)} - \mathrm{E}\left(\tilde{H}_c\right)\right]^2 \cdot p^{(k)} \end{cases}. \tag{4}$$

When using continuous probability hesitant fuzzy semantic tags for information representation, the sum of interval probability values corresponding to a certain semantic tag is not equal to 1. If semantic calculations are performed directly, errors will occur due to incomplete probability distributions. Referring to the basic belief assignment (BBA) idea in evidence theory, reliability can be assigned to single, common and the whole identification framework in evidence theory. Here, the residual probability is assigned to the whole label interval $\tilde{h}_\tau = [s_{-\tau}, s_\tau]$, which is called the normalization of label probability. Then the expectation and variance after CPHFLTS normalization can be expressed as

$$\begin{cases} \mathrm{E}\left(\tilde{H}_c\right) = \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} \tilde{h}_c^{(k)} \cdot p^{(k)} + \tilde{h}_\tau \cdot \left(1 - \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} p^{(k)}\right) \\ \mathrm{D}\left(\tilde{H}_c\right) = \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} \left[\tilde{h}_c^{(k)} - E\left(\tilde{H}_c\right)\right]^2 \cdot p^{(k)} + \\ \qquad \left[\tilde{h}_\tau - \mathrm{E}\left(\tilde{H}_c\right)\right]^2 \cdot \left(1 - \sum\limits_{k=1}^{\left|\tilde{H}_c(p)\right|} p^{(k)}\right) \end{cases}. \tag{5}$$

Definition 3 Assuming that the probability tag values of two CPHFLTS are $\tilde{h}_c^{(i)}|(p^{(i)})$ and $\tilde{h}_c^{(j)}|(p^{(j)})$ respectively, the tag efficiency value distance is defined as

$$\begin{gathered} d_Q\left(\tilde{h}_c^{(i)}|(p^{(i)}), \tilde{h}_c^{(j)}|(p^{(j)})\right) = \\ d_Q\left[Q\left(\tilde{h}_c^{(i)}|(p^{(i)})\right) - Q\left(\tilde{h}_c^{(j)}|(p^{(j)})\right)\right] = \\ d_Q\left[\tilde{h}_c^{(i)} \cdot p^{(i)} - \tilde{h}_c^{(j)} \cdot p^{(j)}\right] = \\ d_Q\left\{[s_{Li}, s_{Ui}] \cdot p^{(i)} - [s_{Lj}, s_{Uj}] \cdot p^{(j)}\right\} = \\ \left[\frac{Li}{2\tau} \cdot p^{(i)} - \frac{Lj}{2\tau} \cdot p^{(j)}, \frac{Ui}{2\tau} \cdot p^{(i)} - \frac{Uj}{2\tau} \cdot p^{(j)}\right]. \end{gathered} \tag{6}$$

Definition 4 Based on the probability tag effectiveness value distance, the tag effectiveness distance between CPHFLTS $\tilde{H}_{c1}$ and $\tilde{H}_{c2}$ is defined as

$$\begin{gathered} d_Q\left(\tilde{H}_{c1}, \tilde{H}_{c2}\right) = \frac{1}{\left|\tilde{H}_{c1}\right| \cdot \left|\tilde{H}_{c2}\right|} \cdot \\ \sum_{i=1}^{\left|\tilde{H}_{c1}\right|} \sum_{j=1}^{\left|\tilde{H}_{c2}\right|} d_Q\left(\tilde{h}_{c1}^{(i)}|(p_1^{(i)}), \tilde{h}_{c2}^{(j)}|(p_2^{(j)})\right) = \\ \frac{1}{\left|\tilde{H}_{c1}\right| \cdot \left|\tilde{H}_{c2}\right|} \sum_{i=1}^{\left|\tilde{H}_{c1}\right|} \sum_{j=1}^{\left|\tilde{H}_{c2}\right|} \left[\frac{L_{c1}}{2\tau} \cdot p^{(i)} - \right. \\ \left. \frac{L_{c2}}{2\tau} \cdot p^{(j)}, \frac{U_{c1}}{2\tau} \cdot p^{(i)} - \frac{U_{c2}}{2\tau} \cdot p^{(j)}\right]. \end{gathered} \tag{7}$$

Equation (7) is the interval distance. For the calculation of the interval distance, the Minkowski norm distance can be used, and (7) can be further expressed as

$$\begin{gathered} d_Q\left(\tilde{H}_{c1}, \tilde{H}_{c2}\right) = \\ \left\{\left[\frac{1}{\left|\tilde{H}_{c1}\right| \cdot \left|\tilde{H}_{c2}\right|} \sum_{i=1}^{\left|\tilde{H}_{c1}\right|} \sum_{j=1}^{\left|\tilde{H}_{c2}\right|} \left(\frac{L_{c1}}{2\tau} \cdot p^{(i)} - \frac{L_{c2}}{2\tau} \cdot p^{(j)}\right)\right]^q + \right. \\ \left. \left[\frac{1}{\left|\tilde{H}_{c1}\right| \cdot \left|\tilde{H}_{c2}\right|} \sum_{i=1}^{\left|\tilde{H}_{c1}\right|} \sum_{j=1}^{\left|\tilde{H}_{c2}\right|} \left(\frac{U_{c1}}{2\tau} \cdot p^{(i)} - \frac{U_{c2}}{2\tau} \cdot p^{(j)}\right)\right]^q \right\}^{\frac{1}{q}} \end{gathered} \tag{8}$$

where $q \geqslant 1$, if $q = 1$, it is Manhattan distance, if $q = 2$, it is Euclidean distance. In this paper, $q = 2$.

Definition 5 For the continuous interval semantic random variable $\tilde{H}_c$, its possible value is interval $\tilde{h}_c^{(k)} = [s_{(k)L}, s_{(k)U}]$, and the corresponding probability distribution is $P(\tilde{H}_c = \tilde{h}_c^{(k)}) = p^{(k)}$, then the reliability of the continuous interval semantic random variable $\tilde{H}_c$ is

$$\mathrm{Rel}\left(\tilde{H}_c\right) = \left(\frac{\sum_{k=1}^{|\tilde{H}_c|}\left(s_{(k)U} - s_{(k)L}\right)\cdot p^{(k)}}{|\tilde{H}_c|}\right)^{\frac{1}{|\tilde{H}_c|}}. \tag{9}$$

4. Fusion recognition method

After the continuous probabilistic hesitation fuzzy semantic label representation and the measurement distance are given, the fusion recognition method of sensor data and expert knowledge can be designed under the framework of belief rules.

This section first presents the belief rule structure based on the IF-THEN rule, which is an expression that can provide closer to the actual knowledge. Secondly, for the rule consequent part, the method of generating the belief of the conclusion by information integration is given. By calculating the correlation between the input sample and the rules in the BRB, and performing the Shafer evidence discount operation, the principle of maximum belief is used to make identification decisions. Finally, the whole process of algorithm implementation is given.

Fig. 2 shows the structure diagram of the heterogeneous information fusion recognition method based on belief rule structure.

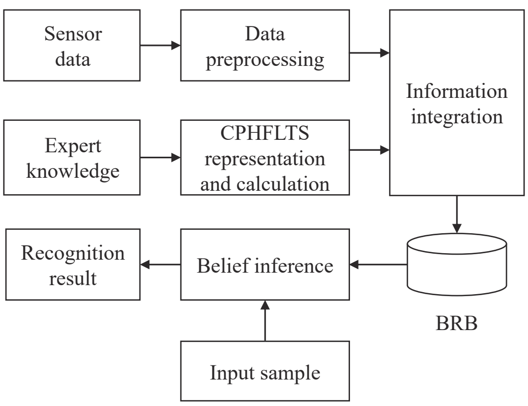

Fig. 2 Structure diagram of heterogeneous information fusion recognition method based on belief rule structure

4.1 Belief rule structure

When constructing RBM, rules are generally obtained from experts or domain knowledge to form a knowledge base, and then effective inference engine is designed to realize inference of observation information, and finally a conclusion is reached [22]. In practical engineering application, the information shows as fuzzy uncertainty, incompleteness, probability uncertainty, etc. This leads to a greater need for the ability to process uncertain information, and the traditional production rules are gradually expanded into fuzzy rules and belief rules [23].

Belief rule structure [24–28] is an extension of the traditional rule-based system and can represent more complex causal relationship. When establishing belief rules, it is necessary to transform qualitative and quantitative knowledge into linguistic variables and fuzzy sets. Linguistic variables are composed of semantic terms. In the actual system, there are many kinds of uncertain information, such as “the possibility that John is very young is 0.8”, the word “young” is a fuzzy expression of age with fuzzy uncertainty, while “0.8” is the certainty of information with probability uncertainty. Therefore, traditional fuzzy rules can describe and deal with fuzzy uncertainties, but they are difficult to deal with probabilistic uncertainties. As a modeling and reasoning method to describe uncertain information, belief rules can provide a more reliable description of knowledge in the application of target intention recognition. An example can be used to illustrate the difference between traditional IF-THEN rules and belief rules. Belief rules can reflect uncertain and incomplete expert judgment in rule conclusions.

IF-THEN rule:

IF Age=30 AND Smoker=Yes THEN Risk=High.

A belief rule:

IF Age=30 AND Smoker=Yes THEN Risk={(High: 50%), (low:30%)}.

For the model based on the IF-THEN rule, its rule k can be expressed as

$$R^k: \quad \text{IF } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \wedge \cdots \wedge x_{T_k} \text{ is } A_{T_k}^k, \text{THEN } \omega_k.$$

A BRB usually consists of a series of belief rules, the k belief rule R^k can be expressed as

$$R^k: \text{IF } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \wedge \cdots \wedge x_{T_k} \text{ is } A_{T_k}^k, \text{THEN}$$
$$\left\{\left(\omega_1,\beta_1^k\right),\left(\omega_2,\beta_2^k\right),\cdots,\left(\omega_N,\beta_N^k\right)\right\},\left(\sum_{n=1}^{N}\beta_N^k \leqslant 1\right)$$

with a rule weight $\theta^k (k = 1, 2, \cdots, L)$ and attribute weights $\delta_i (i = 1, 2, \cdots, T_k)$.

$x_i (i = 1, 2, \cdots, T_k)$ is the precondition attribute, $A_i^k (i = 1, 2, \cdots, T_k)$ is the reference value of the ith precondition attribute x_i in the kth rule, T_k is the number of precondition attribute in the kth rule, θ^k describes the credibility of the rule R^k, called the rule weight, $\delta_i (i = 1,2,\cdots,T_k)$ describes the difference in importance of different precondition attributes in determining the classification result, which is called attribute weight, $0 \leqslant \beta_n^k \leqslant 1$ $(n = 1,2,\cdots,N)$ is the belief assigned to the nth class ω_n in the kth rule [29]. The integrity of the conclusion part of a belief rule depends on whether there is ignorance in the belief distribution of its consequent. $\sum_{n=1}^{N}\beta_n^k < 1$ means that the kth rule is incomplete. The residual belief $1-\sum_{n=1}^{N}\beta_n^k$ represents the global uncertainty of the kth rule. The belief rule structure describes the mapping relationship from input to output classification result. Compared with the traditional IF-THEN rules, it provides a more realistic way of expressing knowledge.

4.2 Information integration

To classify target intention, a BRB that can describe the relationship between input and output should be constructed based on training data and semantic information [30]. Belief rule structure includes rule antecedents, rule consequents, rule weights and feature weights. Rule antecedents, rule weights and feature weights are not the focus of this paper. This paper mainly focuses on the fusion recognition of data from sensors and semantic information from experts. Therefore, we focus on the method of using information integration to generate the belief of the conclusion in the consequent part of the rule.

Calculate the matching degree $\mu(\boldsymbol{x}_i)$ between input $\boldsymbol{x}_i$ and different fuzzy partitions

$$\mu_{A^k}(\boldsymbol{x}_i) = \left(\prod_{j=1}^{T_k}\mu_{A_j^k}(x_{ij})\right)^{\frac{1}{T_k}} \tag{10}$$

where $\mu_{A_j^k}(\cdot)$ is the membership function corresponding to the fuzzy set A_j^k. In order to generate a consequent part with a belief distribution, the training samples $\boldsymbol{x}_i$ assigned to the premise fuzzy region $\boldsymbol{A}^k$ of the rule need to be fused. For the consequent part, the evidence theory is used for information integration. Considering the category set $\Omega = \{\omega_1,\omega_2,\cdots,\omega_N\}$ as an identification framework, the sample $\boldsymbol{x}_i$ belonging to the category ω_n can be regarded as an evidence supporting ω_n as the consequent part of the corresponding rule. In addition to the sample attributes based on data, there are also sample attributes based on continuous interval semantic information in the input, so the two should be integrated to obtain the degree of support for the conclusion.

Due to the uncertainty of the training sample data, this evidence is not completely reliable, and the residual belief can be allocated to the whole identification framework Ω. It can be represented by the mass function m_i^k.

$$\begin{cases} m_i^k(\{\omega_n\}) = \mu_{A^k}(x_i)\cdot \mathrm{Rel}\left(\tilde{H}_c\right) \\ m_i^k(\Omega) = 1-\mu_{A^k}(x_i)\cdot \mathrm{Rel}\left(\tilde{H}_c\right) \\ m_i^k(A) = 0,\ \forall A \in 2^{\Omega}\setminus\{\Omega,\{\omega_n\}\} \end{cases} \tag{11}$$

In order to obtain the conclusion corresponding to the antecedent part $\boldsymbol{A}^k$, the mass function can be integrated based on Dempster rule. The belief of each category in the conclusion part of rule R^k is

$$\begin{cases} \beta_n^k = m^k(\{\omega_n\}),\ \ n = 1,2,\cdots,N \\ \beta_\Omega^k = m^k(\Omega) \end{cases} \tag{12}$$

where β_Ω^k represents the belief that it is not assigned to any individual class ω_n. The belief level corresponding to the conclusion part of the rule not only integrates the contribution values of different sensor data samples according to the matching degree, but also integrates the belief level of the continuous interval semantic random variable $\tilde{H}_c$. The Dempster combination rule is used to realize the information fusion integration of sensor data and expert semantic samples in the consequent part of belief rule structure, so that the training sample information can be used more comprehensively.

4.3 Belief inference

Definition 5 The input sample to be recognized is $\boldsymbol{y}(y_1,y_2,\cdots,y_{T_k})$, $\mu_{A^k}(\boldsymbol{y})$ represents the matching degree between the input sample and each rule in the BRB, δ_p represents the weight of the pth feature, θ^k is the rule weight, S' represents the set of rules activated by the input sample $\boldsymbol{y}$, $S' = \{R^k \mid \mu_{A^k}(\boldsymbol{y}) \neq 0, k = 1,2,\cdots,K\}$. Then the correlation between the input sample $\boldsymbol{y}$ and the activated rule S' is defined as

$$\alpha^k = \mu_{A^k}(\boldsymbol{y})\cdot\theta^k\cdot\left[1-d_Q^k\left(\tilde{H}_{c1},\hat{H}_{c2}\right)\right],\ \ \forall R^k \in S' \tag{13}$$

where $\mu_{A^k}(\boldsymbol{y})$ is represented as

$$\mu_{A^k}(\boldsymbol{y}) = \left(\prod_{p=1}^{T_k}\left[\mu_{A_p^k}(y_p)\right]^{\delta_p}\right)^{\frac{1}{T_k}}. \tag{14}$$

The degree of association represents the validity of the conclusion part of the activated rule for the input sample $\boldsymbol{y}$. In order to reflect the effect of correlation degree on the classification results in the process of evidence reasoning, the Shafer evidence discount operation is used. Shafer evidence discounting is a reliability evidence discounting method proposed for incompletely reliable information [31–33].

Definition 6 [34] Suppose m is the mass function based on the identification framework Ω, and $\alpha \in [0,1]$ is the reliability of the evidence, then the new mass function ${}^{\alpha}m$ obtained after the Shafer discount operation is

$$ {}^{\alpha}m(A) = \begin{cases} \alpha m(A), & A \neq \Omega \\ \alpha m(\Omega) + (1-\alpha), & A = \Omega \end{cases}. \tag{15}$$

Under the belief rule structure, the correlation degree α can be regarded as the reliability of the evidence, Shafer discount operation is performed on the consequent part of each activation rule

$$\begin{cases} {}^{\alpha}m^k(\{\omega_n\}) = \alpha \cdot \beta_n^k \\ {}^{\alpha}m^k(\Omega) = (1-\alpha) + \alpha \cdot \beta_\Omega^k \end{cases}. \tag{16}$$

The mass function is fused using the Dempster combination rule, let m_n^k and m_Ω^k represent ${}^{\alpha}m^k(\{\omega_n\})$ and ${}^{\alpha}m^k(\Omega)$ respectively. The analytical expression for K' combination rules can be written in the following form:

$$m(\omega_n) = J\left(\prod_{k=1}^{K'}\left(m_n^k + m_\Omega^k\right) - \prod_{k=1}^{K'} m_\Omega^k\right), \tag{17}$$

$$m(\Omega) = J\prod_{k=1}^{K'} m_\Omega^k, \tag{18}$$

$$J = \left[\sum_{n=1}^{N}\left(\prod_{k=1}^{K'}\left(m_n^k + m_\Omega^k\right)\right) - (N-1)\prod_{k=1}^{K'} m_\Omega^k\right]^{-1}. \tag{19}$$

The identification decision is made by using the principle of the maximum belief, and the identification result is expressed as

$$\omega = \arg\max_{\omega_n}\{m(\omega_n), m(\Omega)\}. \tag{20}$$

4.4 Algorithm implementation process

For target intent recognition, some attributes are sensor data and some attributes are expert knowledge, but these two kinds of information are independent and complementary. This requires an efficient algorithm that can integrate these two different types of information. Based on the belief rule structure, the algorithm in this paper can fuse heterogeneous information and integrate their respective advantages to obtain better classification results. The algorithm steps are as follows.

Step 1 Expert knowledge is represented by continuous hesitant fuzzy semantic labels. Integrate the semantic label data with the sensor data set to form the attribute description of the target. Then the integrated dataset is divided into training set and test set.

Step 2 The feature space is partitioned fuzzy and the BRB is constructed. In the absence of prior knowledge of the feature space, the fuzzy grids method [35] is used to divide the feature space. This division method is only related to the value range of the feature and the number of divisions.

Step 3 Build a BRB based on the training data set integrated in Step 1. The BRB can reflect the input-output relationship between the training data feature space and the category space. The antecedent part of the belief rule is constructed by the method of fuzzy rules.

Step 4 Calculate the matching degree $\mu(\boldsymbol{x}_i)$ between the input $\boldsymbol{x}_i$ and different fuzzy partitions.

Step 5 Calculate the reliability $\mathrm{Rel}\left(\tilde{H}_c\right)$ of a continuous interval semantic random variable $\tilde{H}_c$.

Step 6 The conclusion part of the belief rule is implemented by using the method described in Subsection 4.2 for information integration. The mass function uses the Dempster combination rule to fuse to obtain the belief β_n^k and global belief β_Ω^k of a certain category ω_n.

Step 7 Compute the degree of association between the input sample and the activated rule, and treat it as evidence. Evidence reasoning is carried out on the conclusion part of all activation rules under the framework of belief rules, and then the category of input samples is judged.

5. Simulation experiment analysis

In this section, two groups of simulation experiments are designed. The first group is the CPHFLTS credibility numerical experiment, which is used to verify the distance measure of continuous hesitation fuzzy semantic label effectiveness and credibility. The second group is the heterogeneous information fusion recognition experiment, which mainly uses the CPHFLTS-BRB method proposed in Subsection 4.4 to solve the problem of target intention recognition, so as to verify its effectiveness.

5.1 CPHFLTS reliability numerical experiment

In the process of establishing BRB, in addition to the attributes of sensor data samples, continuous interval semantic information needs to be integrated, so as to reflect all the attributes of input samples. Due to the influence of various factors, the system input information presents uncertainty. Under the condition of seven semantic labels $S = \{s_i \mid i = -3,-2,-1,0,1,2,3\}$, the continuous probability hesitant fuzzy label is used to describe semantic information.

In the case that the sum of CPHFLTS probabilities is not 1, probability normalization is firstly carried out to obtain normalized semantic label values. Finally, the credibility of CPHFLTS is obtained by calculation. According to the numerical experiment in Table 1, the reliability of corresponding CPHFLTS values can be correctly obtained through the reliability numerical experiment.

Table 1 CPHFLTS values and reliability

CPHFLTS original value	Value of CPHFLTS after normalization	CPHFLTS credibility
$\{[s_{0.5},s_1]\|(0.2)\},\{[s_{1.2},s_{1.8}]\|(0.2)\},\{[s_{2.1},s_{2.8}]\|(0.5)\}$	$\{[s_{0.5},s_1]\|(0.2)\},\{[s_{1.2},s_{1.8}]\|(0.2)\},\{[s_{2.1},s_{2.8}]\|(0.5)\},\{[s_{-3},s_3]\|(0.1)\}$	0.5749
$\{[s_{-1.8},s_{-1}]\|(0.2)\},\{[s_{-0.8},s_{0.9}]\|(0.7)\},\{[s_{1.1},s_{1.5}]\|(0.1)\}$	$\{[s_{-1.8},s_{-1}]\|(0.2)\},\{[s_{-0.8},s_{0.9}]\|(0.7)\},\{[s_{1.1},s_{1.5}]\|(0.1)\}$	0.7738
$\{[s_{-1.4},s_{-1.2}]\|(0.1)\},\{[s_{0.4},s_{1.1}]\|(0.3)\},\{[s_{0.8},s_{1.7}]\|(0.4)\}$	$\{[s_{-1.4},s_{-1.2}]\|(0.1)\},\{[s_{0.4},s_{1.1}]\|(0.3)\},\{[s_{0.8},s_{1.7}]\|(0.4)\},\{[s_{-3},s_3]\|(0.2)\}$	0.5815
$\{[s_{-2.6},s_{-1.5}]\|(0.3)\},\{[s_{0.5},s_{0.7}]\|(0.5)\},\{[s_{2.4},s_{2.6}]\|(0.1)\}$	$\{[s_{-2.6},s_{-1.5}]\|(0.3)\},\{[s_{0.5},s_{0.7}]\|(0.5)\},\{[s_{2.4},s_{2.6}]\|(0.1)\},\{[s_{-3},s_3]\|(0.1)\}$	0.5313

5.2 Heterogeneous information fusion recognition experiment

The characteristic attribute data $(x_{i1},x_{i2},\cdots,x_{iN})$ of each sample $\boldsymbol{x}_i=(x_{i1},x_{i2},\cdots,x_{iM})$ is obtained by the sensor. In order to better represent the uncertainty of expert knowledge, the characteristic attribute $(x_{i(N+1)},x_{i(N+2)},\cdots,x_{iM})$ is represented by the continuous probabilistic hesitation fuzzy semantic label proposed in this paper. The task of a fusion center is to classify and recognize the target intention after receiving the data of target detection by sensors and the judgment made by experts. According to the proposed method of heterogeneous information fusion recognition based on belief rule structure, the two kinds of information are used for intention recognition.

Step 1 The amplitude range is obtained by processing the characteristic attribute value $(x_{i1},x_{i2},\cdots,x_{iN})$ of the data obtained by the sensor, the data of training set and test set are normalized.

Step 2 Determine the attribute fuzzy region of sensor data, and set the number of fuzzy region division as C. The membership value of the training sample is calculated according to the membership function $\mu_{A_j^k}(\cdot)$ corresponding to fuzzy set A_j^k. By comparing the membership degree values, we can determine which fuzzy region the characteristic attribute values of a training sample fall into and give corresponding marks.

Step 3 Expert knowledge is described by CPHFLTS random variable $\tilde{H}_c$. On the basis of normalizing the probability of $\tilde{H}_c$ label, the reliability $\mathrm{Rel}\left(\tilde{H}_c\right)$ is obtained by calculating the label efficiency value.

Step 4 Fusion processing is performed on the training samples $\boldsymbol{x}_i$ assigned to the premise fuzzy area $\boldsymbol{A}^k$ of the rule R^k, and the conclusion part with the belief distribution is obtained. Integrate the membership degree $\mu_{A^k}(\boldsymbol{x}_i)$ of the sensor data attribute and the credibility $\mathrm{Rel}\left(\tilde{H}_c\right)$ of the CPHFLTS information attribute, and get the belief β_n^k for the support degree of category ω_n. Loop Step 2−Step 4 to establish a BRB.

Step 5 Calculate the degree of association between the input sample $\boldsymbol{y}$ and the activated rule S', Shafer discount operation is performed on the consequent part of each activation rule, the Dempster combination rule is used to fuse the mass function to obtain the belief of each category, the identification decision is made by using the principle of the maximum belief.

Table 2 gives the belief values and recognition results of different categories corresponding to different sample inputs.

Table 2 Belief and recognition results corresponding to different input samples

Input sample	Class ω_1 belief	Class ω_2 belief	Class ω_3 belief	Recognition result
y_1	0.5449	0	0.0864	1
y_2	0.3284	0.1691	0.4267	3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
y_{10}	0	0	0.2961	3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
y_{18}	0.2299	0.2938	0	2

In order to verify the classification and recognition ability of the algorithm under different conditions, different noise levels are set for the training data set, it is used to simulate the unreliability of data in the actual environment, that is, the category annotation of some samples is wrong. The identification errors of support vector machine (SVM), C4.5 [36,37], fuzzy rule-based classification system (FRBCS) [38], data-driven BRB classification system (DBRBCS) and the CPHFLTS-BRB method proposed in this paper are compared and tested. Fig. 3 shows the classification and recognition errors of the corresponding methods under different noise levels in the training data set. As can be seen from the figure, classification errors of SVM, C4.5 and other methods increase with the increase of noise level, SVM and C4.5 have large classification errors, the DBRBCS method maintains good robustness, and the FRBCS method always has moderate identification errors. Compared with other methods, the CPHFLTS-BRB method proposed in this paper maintains low classification errors under different noise levels, although it is also affected by noise levels.

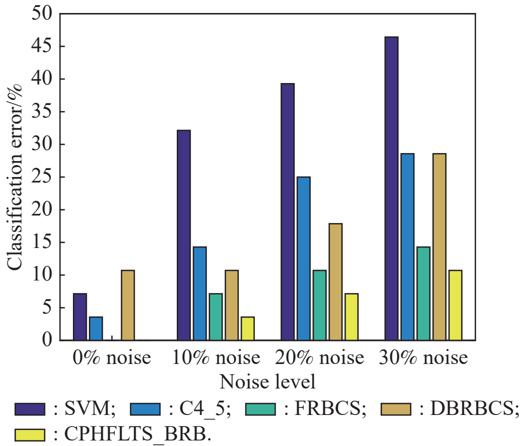

Fig. 3 Classification errors at different noise levels

6. Conclusions

To solve the problem of target intention recognition in multi-source information fusion, this paper proposes a heterogeneous information fusion recognition method based on belief rule structure. This method can effectively use sensor data and expert knowledge information for fusion recognition. It provides an effective solution to the problem of the identification of uncertain sensor data and expert knowledge in practical applications. The CPHFLTS reliability numerical experiment is designed to verify the validity of the continuous hesitation fuzzy semantic label distance measure method. The CPHFLTS-BRB method is demonstrated through an application of multi-source target intent recognition. It can be seen from the experimental results that the CPHFLTS-BRB method proposed in this paper can effectively utilize sensor data and expert knowledge, which are two independent and complementary information, and improve the level of target intention recognition. In the actual environment, the measured data and the corresponding expert knowledge for a specific target may be incomplete, so how to process the incomplete information to obtain the target intention is the next research direction.

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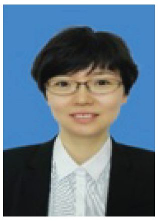

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