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TARGET RECOGNITION BASED ON ROUGH SET WITH MULTI-SOURCE INFORMATION

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Abstract- As the attributes provided by multi-source information can be used to distinguish between the different species of targets, attributes recognition becomes the most important work in target recognition. In this paper, a new method for attributes recognition was proposed with rough set theory. It used a new way to described the target with a information system consisting of four elements, reduced the attribute value according to the mission requirements, valuated the attribute based on the degree of importance, and recognized targets by the sum of valuation. Finally, a set of experiments were designed to demonstrate the effectiveness of the proposed method. Furthermore, the factors that would affect the performance of the recognition system were discussed.

Index terms: recognition; Rough Set; attribute mathematics; multi-source information;

I. INTRODUCTION

Target recognition is a common problem in the modern information society, such as the identification of customers by unattended automatic teller machine and identification friend or foe in the complex battlefield environment. The repeatability, inaccuracy, and deception in the information make it difficult to recognize the target exactly. Usually in broader terms, the process of target recognition can be divided into three layers: discrimination, classification, and identification. Through discrimination, we can obtain the differences between the various targets. Classification means to differentiate the categorical attributes, and identification is a description of the specific characteristics. In this paper, we will discuss the target recognition in the narrow sense, which is target identification. The technology of target recognition includes the research on how to efficiently make use of all information of sensors, gathering the the proper recognition signal from our physical world, obtaining and detecting the identification information by computer information process technology, and describing the various features by mathematical models. There are kinds of target recognition systems, such as radio frequency identification system, radar target recognition system, electronic support measurements, infrared sensor decision support system, and so on.

In general, the identification ability of a single sensor is limited. The effective way to improve the accuracy of target recognition is to increase the available target information from multi-source, which can be called identification with multi-attribute. Using the information form multi-source, we can access multi-attribute descriptions of targets. By combination of attributes, we can describe the target in greater detail, so as to attain a more accurate recognition result. In essence, identification with multi-attribute means the process of integrating multi-source information. In the field of target recognition technology, the main mathematical analysis methods include The Bayes estimation [1], DS evidence theory [2], fuzzy set theory [3-8], neural networks [9-15], artificial intelligence technology [16], rough set theory [17-21], and so on.

The Bayes estimation is founded on the Bayes statistics theory. The basic idea of it is treating a unknown parameter as a random variables with a certain probability distribution. This probability distribution contains the information of unknown parameter before sampling, which is called the prior distribution. This reasoning technique is often used for information fusion, through synthesis a posterior distribution with prior distribution and the information of samples, propose a probabilistic recognition for targets.

DS evidence theory is the result of the work multi-valued mapping by Dempster in 1960. In its original expression, it provided a general framework for uncertainty reasoning model by combining the confidence function with the upper and lower values of probability. Later in 1970, the DS theory is expanded by Shafer, which prompted the framework. In fact, DS evidence theory can be recognized as a generalized Bayes estimation. It adopts interval uncertain probability knowledge to discuss the likelihood function under multi assumption information. In this theory, the information form sensor is called the evidence, and it constructs a confidence coefficient for each hypothesis. The combination of Probability distribution function and its corresponding resolution law is seen as a body of evidence. And the data fusion with multi-source information is the process to integrate the independent information into entire integrated evidence, which is called DS data fusion.

The fuzzy set theory determines the subordinate relations among different set based on generalized fuzzy set theory. The fuzziness of information in data fusion makes it difficult to describe the target. However, it can make a classification and recognition. It can confirm the fuzzy subset relationship between the standard detected target and the target to be recognized. The specific analysis methods include fuzzy set pair analysis, fuzzy decision-making, and fuzzy set and fuzzy measure. In these methods, the idea based on fuzzy set and fuzzy measure not only considers the data from different sensors, but also takes care of the credibility of the data from various sensors, which is the main reference for this paper.

The neural network theory results from the research of biological neural information processing system. In this theory, the classification from data to attribute can be got by a nonlinear vector transformation of the input information. Several neural networks can translate the information form multi sensors to an entire attribute description of target. This method can be used to deal with targets with complex attributes. However, the recognition process of it is more complex, and it may cost much more time.

II. OVERVIEW OF ROUGH SET AND TARGET RECOGNITION

A. Attribute Mathematics and Rough Set Theory

Attribute mathematics is a useful method to solve the problem of attributes modeling, classification, and decision. Based on the physical characteristics of target, the basic methods in attribute mathematics can be divided into four categories, namely, certainty analysis founded on the traditional set theory, random analysis founded on probability (Bayes), fuzzy analysis founded on fuzzy math, and rough analysis founded on rough set theory.

Multiple attribute recognition system is a relatively complex and strong real-time decision-making activity. In the multiple attribute recognition, the more accurate judgment can be made with more information. But too much information will affect the real-time of identification. Therefore, based on the analysis of the factors influencing the target attribute identification, we need choose the proper attribute information according to the differences of each attribute. The recognition system with multiple attribute should have the capacity of selecting the appropriate attribute set according to the different application environment. On the basis of uncertainty measurement theory, we can suppose that, in a basic multiple attribute recognition system, a attribute set I that includes all potential issues can be designed in accordance with the expert opinions and available information, $I = \{I_1, I_2, ..., I_n\}$. Corresponding to each specific task, an attribute value of matrix $V(I)$ can be defined:

$$V(I) = \begin{bmatrix} v(I)_{1,1} & ... & v(I)_{1,m} \\ ... & ... & ... \\ v(I)_{n,1} & ... & v(I)_{n,m} \end{bmatrix} \tag{1}$$

In (1), $v(I)_{ij}$ represents the possible values of j in attribute I_i . By sorting the possible values of attribute form lowest to highest, a new matrix $V(I)^{'}$ can be obtained:

$$V(I)^{'} = [v(I)^{'}_{i,j}]_{n\times m},\quad v(I)^{'}_{i,j} < v(I)^{'}_{i,j+1} \tag{2}$$

Using the formula $E(I_i) = \sum_{j=1}^{m-1} (v(I)^{'}_{i,j} - v(I)^{'}_{i,j+1}) \ln j$, we can calculate the undesignated attribute set $E = \{E\{(I_i)\}_{i=1:n}$. If $E\{(I_i) = \ln s$, remove the attribute I_i . Then we can get the attribute set $I^t = \{I^t_k\}_{k\le n}$ for the task t .

Rough Set theory was first put forwarded in 1982, which can deal with problem of vagueness and uncertainty. The advantages of Rough Set theory is mainly embodied in that it does not need a priori or additional information about the data, and it can deal with the uncertainty problem by use strict mathematical method, which provides a solid foundation for the development of rough set theory. Rough Set theory processes information from the point of cognitive science, which makes it widely used in the field of inference, economic decision and so on. As any target can be described by some knowledge, according the knowledge, targets can be divided into different classes using the corresponding knowledge of attributes description.

Suppose we use $U = \{x_1, x_2, ... x_8\}$ to describe a set of construction toys, which have different color (red, yellow, and blue), shape (square, circle, and triangle), and volume (large and small).

As a result, these construction toys can be described using the knowledge of color, shape, and volume, and we can get a description of these construction toys according to a particular attribute.

Sorted by color:

$\{red \to x_1, x_3, x_7\}, \{blue \to x_2, x_4\}, \{yellow \to x_5, x_6, x_8\}$.

Sorted by shape:

$\{circle \to x_1, x_5\}, \{square \to x_2, x_6\}, \{triangle \to x_3, x_4, x_7, x_8\}$. Sorted by volume:

$\{large \to x_2, x_7, x_8\}, \{small \to x_1, x_3, x_4, x_5, x_6\}$.

In other words, according to the above attributes: color r_1, shape r_2, and volume r_3, we can get the following three categories:

$$IND(r_1) = U / r_1 = \{(x_1, x_3, x_7), (x_2, x_4), (x_5, x_6, x_8)\},$$
$$IND(r_2) = U / r_2 = \{(x_1, x_5), (x_2, x_6), (x_3, x_4, x_7, x_8)\},$$
$$IND(r_3) = U / r_3 = \{(x_2, x_7, x_8), (x_1, x_3, x_4, x_5, x_6)\}.$$

B. Recognition Model

Binary Model: A simplest recognition model contains a collaboration support system, a recognition body, and a recognition system, which is called point to point model. As this model can only deal with the problem of true or false, we also called it binary model. The main characteristic of this model is that, it only can do a one-way recognition, and the communication to target is passive. The decision-making system may have multiple sources, targets, collaborations, and supports, as shown in figure 1. In a real environment, the entrance guard system can be understood as a simple implementation of a target recognition system based on binary model. This system is founded on a simplest collaborative support system, which only use simple authentication information, such as fingerprints, or voice, or a radio frequency card.

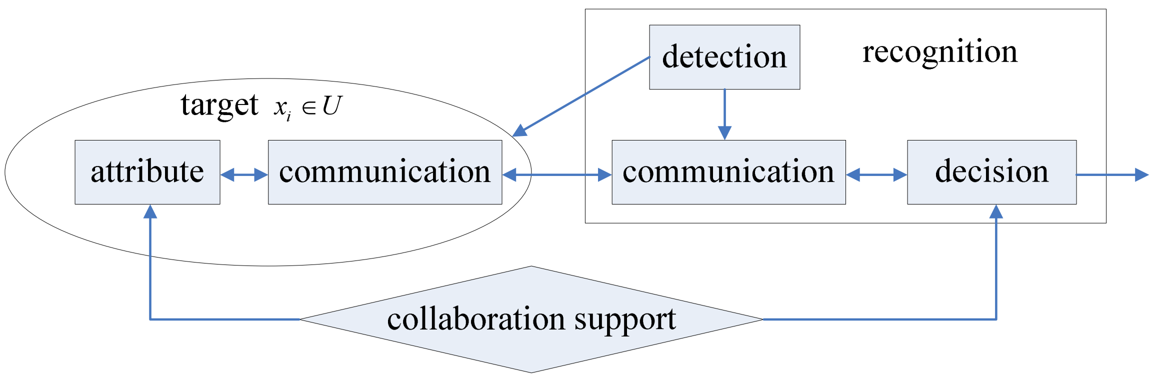

Figure 1. Collaborative binary recognition.

Collaborative Multi-value Model: On the basis of collaborative binary target recognition model, as the attribute of targets can have varieties of value, the recognition system needs more decision-making subsystems. Using this model, we can get a more detailed description of target. Because of the characteristic of non binary value, it needs more decision-making subsystems to match the various attributes, as shown in figure 2. For example, the electronic library recognition can be seen as this model. Any user's database is the decision-making subsystem of this system. The main subject and object of it are library user login system and request login users.

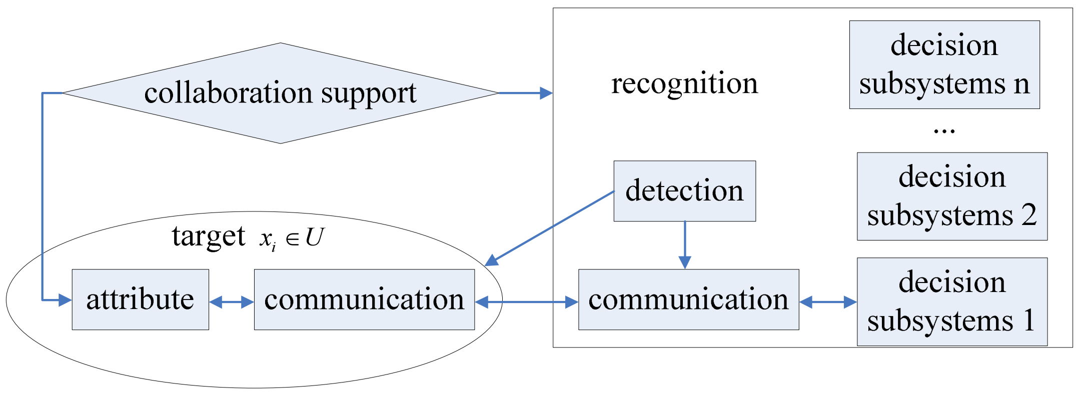

Figure 2. Collaborative multi-value recognition

Collaborative Multi-attributes Model: To increase the reliability of recognition, we can increase target attributes, which can be obtained by multi-source information, as shown in figure 3. By the correlation between attributes, correctness of the information can be verified. In this model, the elements of attribute set can be increased, which can improve the effectiveness of recognition. However, it also increases the difficulty for system to make a decision.

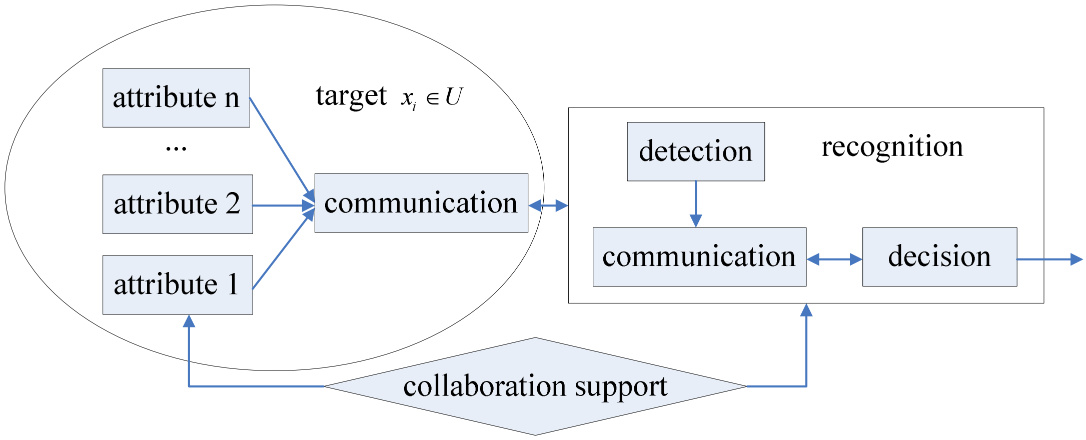

Figure 3. Collaborative multi- attributes recognition

Multi-attributes Model based on Rough Set: From above, it can be seen that the target recognition system is mainly composed of two parts: collaboration support system and the recognition subject and object. As the support system and the decision of subject is based on rough set theory, so we call the model will be used in this paper multi-attributes model based on rough set theory. This model mainly consists of two components: collaborative support system based on rough set and decision-making system. First, we will investigate the collaborative support system. As the core part of this system, it is mainly responsible for selecting the attributes in each task, and makes a unique description of the attributes. In order to make a good use of channel resources, we need decrease the numbers of asking for different recognition. The basic idea of the system is, generating a decision table in the process of task for each subject, and increasing one communication for exchange decision table of them after the identity recognition. As a result, the process of decision table can be constructed more quickly. When the target that need to be recognized are too more, the direct use of decision table can improve the efficiency of recognition observably.

On the basis of this model, the entire recognition process is proposed as follows:

(1) Before each task, collaborative support system provides the prior information to recognition subject, which includes the attributes which are selected, the proper description of each attribute, and the correlation between various attributes;

(2) In the process of task, the subject sends a asking message in the form provided by prior information;

(3) The object gives a reply to the subject;

(4) The subject makes a recognition based on the prior information and the reply, and generates a real-time decision table, which can be used as the instant information and the data for testing the performance of the system.

(5) If the object and subject belong to one set of attributes, then exchange their decision tables. Otherwise, the subject does not send its decision table to the object.

C. Challenges of Current Recognition System

However, there are still some problems in the current target recognition systems with multi-source information:

(1) In the most target recognition, some prior information is requested, such as the prior probability of target motion, target model, group information and so on. But in reality, information can be obtained is limited, which brings lots of challenges in recognition process.

(2) The description method for attributes is increasing. Target recognition system includes information in different areas, such as logic value, numbers, and text. The diverse information makes it much more complex.

(3) The information to be processed becomes of uncertainty and fuzziness. Due to some objective reasons, such as interference or sensor precision, we cannot guarantee the accuracy of collected information.

III. RECOGNITION BASED ON ROUGH SET

A. Modeling forRecognition System

The purpose of recognition is to classify the target with the mathematic description in knowledge base, and get a final qualitative description. It can thus be seen that recognition criteria contains prior information and the specified algorithm. While the recognition algorithm includes two aspects: recognition of attributes space and recognition of measure space. We will propose some criteria models in the following.

The mathematical description of the collaborative binary single attribute target recognition decision. In this model, it includes an attribute space and measurement space that targets could have. A description of the target is denoted by $(x, F(x), u(A))$, where x represents identity information of target, $F(x)$ is the corresponding attribute space, and $u(A)$ represents the measurement space. As there is only one attribute, we have $F(x) = A$, in which A stands for a specific attribute. For this collaborative binary model, we have $u(A) = \{0,1\}$.

The mathematical description of the collaborative multi attributes value target recognition decision. A description of the target is denoted by $(x, F(x), u(A))$. Unlike the model above, the attribute measurement space is multi-value, i.e., $u(A) = \{a_1, a_2, ..., a_n\}$.

Similarly, the decision model of the collaborative recognition based on rough set can be defined. There are mainly three components: prior shared data base, description system, and decision-making system. In the prior shared data base, a specific description of attributes and the value of them are available; we denote it as a data packet, which is defined by a knowledge system $KS = \{F(x), u(F(x))\}$ .The elements of it is defined as follows: $F(x) = \{A_1, A_2, ...A_n\}$ stands for the attribute description; $u(F(x)) = \{u(A_1), u(A_2), ..., u(A_n)\}$ is a description of the target attribute value. In the description system, there is specific mathematic information for every target, which can be formally expressed as $IS = \{U, C, V, f\}$, where $U = \{x_i\}$ is the unique expression of the target attribute; $C = \{a \mid a \in C\}$ stands for the not empty finite set of attribute, in which each a represents a simple attribute of C ; $V = \cup V_j (1 \le j \le m)$ is the range of the information function f, in which V_j stands for the range of attribute a_j ; $f = \{f_i : U \to V_j, (1 \le j \le m)\}$ is the information function of information system IS, where f_i is the function of attribute a_j. In the decision-making system, each target has a unique recognition system that can be distinguished from others, and a mathematical description of it is $DS = \{\Theta, \Phi, E, \vartheta\}$, in which $\Theta = \{x_1, x_2, ..., x_n\}$ is a not empty finite set of the object, where $x_i (1 \le i \le n)$ represents a target; $\Phi = C \cup D (C \cap D = \varnothing)$, in which C is the set of attributes, D is the set of decision-making attributes.

The entire identification process can be described as following:

Step 1: The identification subject x_i sends a request $S_1 = \{x_i\}$ to the object, and asks the object to return its personal information to verify identity.

Step 2: The object x_j deliver a response message $S_2 = IS$ to the subject x_i.

Step 3: According to the response message S_2 and DS, the subject makes recognition of the target, and establishes a decision tables on the basis of the set of decision-making attributes and the recognition result $I(x_j)$. After this step, recognition is completed between two targets. If both of them belong to one category, a communication is set up for exchanging their decision table, and the process goes to next step. Otherwise, the recognition process is completed.

Step 4: The subject sends information $S_3 = IS = \{x_i,\ DT(x_i)\}$ to the objects that belong to the same category.

Step 5: The object gets $DT(x_i)$ form information S_3, and do the operation $DT(x_j) = DT(x_i) \cup DT(x_j)$ to generate a new decision-making table, and return a message $S_4 = \{x_j,\ DT(x_j)\}$ to the recognition subject x_i.

B. Attribute Reduction based on Rough Set

The description of a target can be varied, that is to say, each target has lot of different attributes. However, not every attribute is efficient recognition. Hence the first important problem that needs solving is to select the attributes which are beneficial for us. The main idea of the proposed recognition system is established a basic attribute set, which concludes the possible attributes that the targets may have and are of universality for all tasks. Aiming at particularity of each task, we focus on reduction the attributes of less importance to get an exclusive set for a given task based on previous task information and rough set theory knowledge. Here we will research on several attribute reduction algorithm based on rough set theory.

✧ Attribute Reduction with Blind Deleting

Given an information system $IS = \{U, A, V, f\}$, for each attribute a_i, do the following processes until the attribute set no longer changes: First select an attribute $a_i \in A$, if remove the attribute a_i can make the equation $U / IND(C - \{a_i\}) = U / IND(c)$ true, it means that a_i is not necessary in C and remove the column where a_i lies. Repeat this step until any of the elements cannot be removed, then the current attribute set is a reduction of the information system. Otherwise, it means that the attribute a_i is necessary in C, which is cannot be removed. If any element of C is necessary, then the information system has only one attribute reduction, called the ordinary attribute reduction of the information system.

By above description, let $S \Leftarrow C - \{a_i\}$, then two points can be kept at the end of the above steps: (1) $U / IND(S) = U / IND(C)$; (2) S is independent form each other. It shows that the information system we have obtained must be a reduction one.

Definition 1 (Marking Function $Mark(a)$): If A is a attribute set for a given knowledge expression system, and if $\forall a \in A$, then

$$Mark(a) = \begin{cases} 0, & \text{if a is not accessed yet} \\ 1, & \text{if a is accessed already} \end{cases} \quad (3)$$

By this definition, thus we will propose the specific steps for attribute reduction with blind deleting:

Input: $IS = \{U, A, V, f\}$

Output: A reduction attribute $B \in Red(C)$

Step 1: Let $B = C$

Step 2: $\forall a \in C$, if $a \in B$, then $Mark(a) = 0$

Step 3: Select an attribute $a \in B$ arbitrary. If $Mark(a)$ equals 0, then let $Mark(a)$ equals 1. If $U / IND(B - \{a_i\}) = U / IND(B)$, then remove a from B, i.e., $B \Leftarrow B - \{a\}$ and go to step 2, else go to step 4;

Step 4: If $a \in B$, then $Mark(a) = 0$ and go to step 3, else stop the process and output B.

✧ Reduction based on Importance Degree

In classic set theory and fuzzy set theory, the importance degree of attribute is described a weighting coefficient from experience. In rough set theory, to measure the importance of attribute only needs the information provided by the system itself, in other words, it does not need any other additional auxiliary information. In fact, the importance degree of attribute shows the classification for ability information system of attributes. If remove an attribute in the knowledge expression system, the greater classification ability of the knowledge expression changes means the more important the attribute is. On the other hand, the smaller change means that the attribute is more needless.

We can also use the positive region conception of the knowledge to another to describe the importance degree of attribute. Given any a subset of attribute $B \in (B \subseteq C)$, remove a attribute subset P, then the greater difference between $card(pos - (B - P))$ and $card(pos - B)$ means that removing P will makes a greater effect on the classification ability of B, that is to say, P is of more importance to B. Then the definition of importance with attribute to set of attributes can be proposed, if P is a single attribute.

Definition 2 (Importance Degree of Attribute): Given an information system $IS = \{U, A, V, f\}$, for $\forall B \subseteq C$ and $\forall a \in C - B$, define the importance degree of attribute a to the attribute set B as:

$$sig_{a,B,C} = \frac{card(U / IND(B \cup \{a\})) - card(U / IND(B))}{card(U)} \quad (4)$$

The specific steps for attribute reduction based on importance degree are shown in the following:

Step 1: Calculate the core of the given information system.

Step 2: Let $B = Core(C)$, if $IND(B) = IND(C)$, then go to step 5, else go to step 3.

Step 3: For $\forall a \in B / C$, calculate the importance degree of the attribute $sig_{a,B} = | IND(B \cup (a)) | - | IND(B) |$, and get the value of a_m:

$$a_m = \arg \max_{\forall a_i \in C/B} \{sig_{a_i,B}\} \tag{5}$$

If there are several attributes that satisfy (5), then select the attribute with minimum divided numbers and let $B \Leftarrow B \cup \{a_m\}$.

Step 4: If $IND(B) \neq IND(C)$, then go to step 3, else go to the next step.

Step 5: Output $B \in Red(C)$ and exit.

✧ Reduction based on Skowron Discernibility Matrix

Definition 2: Denote the knowledge expression system by $KRS = (U, A, V, f)$, in which domain of discourse is a finite nonempty set of the object $U = \{x_1, x_2, ... x_n\}$, and the discernibility Matrix of the knowledge expression system is defined as follows:

$$\begin{cases} M_{n\times n} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ * & c_{22} & \cdots & c_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ * & * & \cdots & c_{nn} \end{bmatrix} \\ c_{ij} = \{a \mid (a \in A) \cap (f_a(x_i) \neq f_a(x_j))\} \end{cases} \tag{6}$$

The core of information system of is the entire simple attribute (single attribute) element group. The specific steps for attribute reduction based on Skowron discernibility matrix are shown as follows: First, determine the matrix according to the given information system. Then search all single attribute in the discernibility matrix elements, and assigned them to the core of C. Calculate all the possible attributes combination which contains the core, and determine whether it meets the following condition in (7). If meeting, then assign them to the core of C. At last, Output the core of C and exit.

$$\forall c_{ij} \in M_{n\times n}, if\ c_{ij} \neq \varnothing, then\ B \cap c_{ij} \neq \varnothing \tag{7}$$

Definition 3: Given a knowledge expression $KRS = (U, A, V, f)$, define the discernibility variable between x_i and x_j to attribute α:

$$a(x_i, x_j) = \{a \mid (a \in A) \cap (f_a(x_i) \neq f_a(x_j))\} \tag{8}$$

$$\sum a(x_i,x_j)\begin{cases}\sum a(x_i,x_j)=a_1\cup a_2...\cup a_k\\ 1,\ a(x_i,x_j)\neq\varnothing\end{cases} \tag{9}$$

Then the discernibility function is defined as follows:

$$\Delta=\prod_{\forall(x_i,x_j)\in U\times U}\sum a(x_i,x_j) \tag{10}$$

The specific steps for attribute reduction based on discernibility function are shown in the following:

Step 1: Calculate discernibility matrix;

Step 2: For nonempty set valued elements $c_{ij}\neq\varnothing$, establish the corresponding logical expression $L(IS)$ on the basis of this function:

$$L(IS)=\bigcap_{\forall c_{ij}=a(x_i,x_j)\neq\varnothing\in M_{n\times n}} a(x_i,x_j) \tag{11}$$

Step 3: Through logical operations on the $L(IS)$, get the conjunction normal form, and output the results.

C. Decision Tables Attribute Value Reduction

✧Decision Reduction with Blind Deleting

Given a decision table $DT=\{U,C\cup D,V,f\}$, after attribute reduction, a correlation reduced relational data table $T(B)=\{U_B,B\cup D,V,f\}$, treat each sample in $T(B)$ as a decision rule, then $T(B)$ can be translated to decision rule table. For rule set and each rule r_i, if remove $(a_j^{'},v_{ij})$ from r_i, then remove the same column of the rest of the rules, i.e., there will not incur rules that is incompatible with r_i. Then the value v_{ij} in attribute $a_j^{'}$ is unnecessary for this decision. Otherwise, the necessary value v_{ij} in attribute $a_j^{'}$ cannot be removed. With the above results, remove the other value with different attributes in decision rule, until obtain an absolute reduction rule.

✧Decision Reduction with Induction Value

Definition 4 (Class of Equivalent Decision Rule): Denote $U\,|\,D=\{y_1,y_2,...,y_n\}$ as the set of decision class that divided by attribute decision in domain U, for each class of the equivalent decision, define the equivalent class of decision rule as DRC:

$$DRC(y)=\{d_x : des([x]_c)\Rightarrow des([x]_d)\},\forall y\in U\,|\,D \tag{12}$$

According to the definition 4, solution to the minimum decision algorithm of tables can be turned into calculating the minimum decision for each decision class. The solution to the minimum decision algorithm for each decision class can be realized through deleting the redundancy attribute value and the redundancy rules.

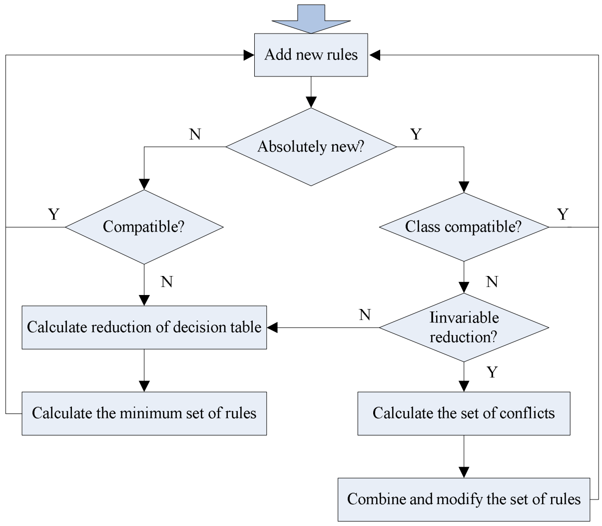

Figure 4. Flowchart of decision reduction with incremental value

✧Decision Reduction with Incremental value

Consider a decision table $DT=(U,V,C\cup D,f)$, after relative attribute reduction and value reduction, a minimum set of rules can be obtained. Denote M as all the rules after reduction. Let $d_x:\phi_x\to\varphi_x$ stands for a new rule. According to the relationship between M and d_x, we have the following two propositions. And the flowchart of decision reduction with incremental value is shown algorithm of in figure 4.

Proposition 1: Denote a relative reduction D for the decision table $DT=(U,V,C\cup D,f)$ by $B\in Red_c(D)$. Let M represent a minimum set of rules for decision table under this relative reduction. The new rule is defined as d_x, and the newly constructed decision table is $DT'=(U\cup\{x\},V,\ C\cup D,\ f)$. Then $B\in Red_c(D)$ is the relative reduction of the new decision table if and only if d_x is compatible or class compatible with M.

Proposition 2: Given a decision $DT=(U,V,C\cup D,f)$, denote a set of rules generated from the rule d_x in M by S. Obviously, we have $S\subseteq M$. Let M' stand for a minimum set of rules for decision table $DT'=(U\cup\{x\},V,C\cup D,f)$, then $S\subseteq M'$, if and only if, $\forall d_r\in S$ if $\phi d_x\to\phi d_r$, then $\varphi d_x=\varphi d_r$.

D. Design of Target Recognition algorithm on the basis of Attribute Measure

Denote the object space to be researched as X, and $x_1, x_2,...,x_n$ are n samples of X. To each sample, m indexes are measured $I_1,I_2,...,I_m$. The measurement of the j th index of the i th sample is x_{ij}. As the properties of samples are absolutely determined by the measurement, we can express a sample by a vector with m dimensions $x_i = \{x_{i1}, x_{i2}, ..., x_{im}\}$. Suppose that there are K evaluation classes or decision C_1, C_2,...,C_K for the elements in X . Then it needs a judgment to decide which class or decision that x_i belongs to.

The above problem can be turned into a comprehensive evaluation system or the comprehensive decision-making problem. The entire system can be divided into three parts: single performance index function analysis subsystem, more comprehensive performance index function analysis system, and recognition subsystem. In this paper, the performance function we used is attribute measure. In general, attribute measure is determined according to the specific problems, the experimental data, expert experience, or certain mathematical processing method.

IV. EXPERIMENTAL TEST AND VALIDATION

A. Test Environment and simulation results

Simulation environment: In Visual C plus plus software environment, use the binary phase shift keying method (BPSK) for signal modulation and demodulation, and adopt the additive white Gaussian noise channel (AWGN) for communication.

Simulation content: Generate 50 targets randomly, and the number of attribute is 20. Through the additive white Gaussian noise channel with different bit error rate, calculate the target recognition probability, and compare the probability between attribute with non-reduction and after attribute reduction. The simulation results are shown as follows.

According to the simulation results in figure 5, figure 6, and figure 7, it concludes that with the same numbers of target, algorithms with attribute reduction greatly reduced the error recognition rates compared to the algorithm with non-reduction. And compare the three recognition algorithm with different reduction methods, we can find that blind reduction and reduction with importance degree have the resemblance performance, and the algorithm with Skowron discernibility matrix reduction has the best performance.

- Attribute Blind Reduction

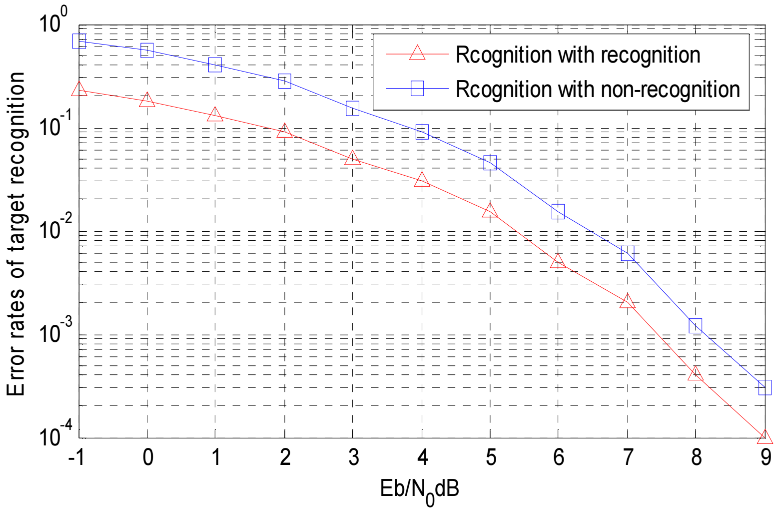

Figure 5. Recognition with attribute blind reduction

✧ Recognition with Importance Degree

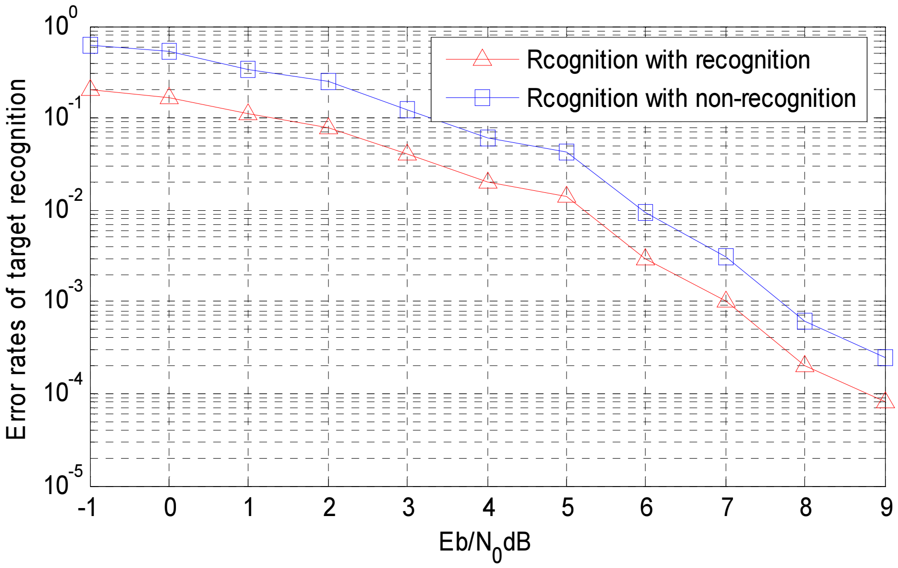

Figure 6. Recognition with importance degree reduction

✧ Recognition with Skowron Discernibility Matrix

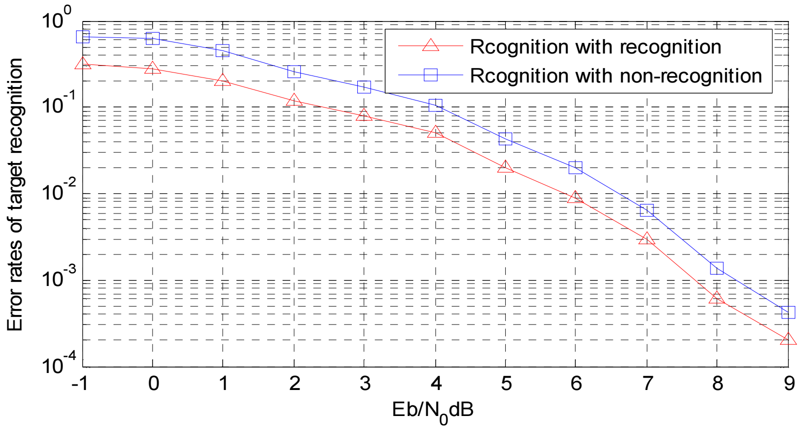

Figure 7. Recognition with Skowron discernibility matrix reduction

B. The effect of target numbers on performances

Next, we will investigate the effect of targets numbers on the performance of these algorithms. In the test, we choose the additive white Gaussian noise channel with 5 dB signal to noise ratio, with the different numbers of target from 2 to 100, so as to observe the effect of numbers on recognition results. The simulation results are shown as follows.

From figure 8, figure 9, and figure 10, we can see that when the numbers of target is less than 20, the error rates of recognition is low. As the target numbers increasing, the error rates of these algorithms show a trend of rising. In general, the performances of algorithm with bind reduction and algorithm with importance degree are similar, which is obvious when the target numbers exceed 50. Moreover, from the above results, curves are of certain stochastic property, which is due to the information of targets is generated in a random way. For this reason, it causes the fluctuant simulation results.

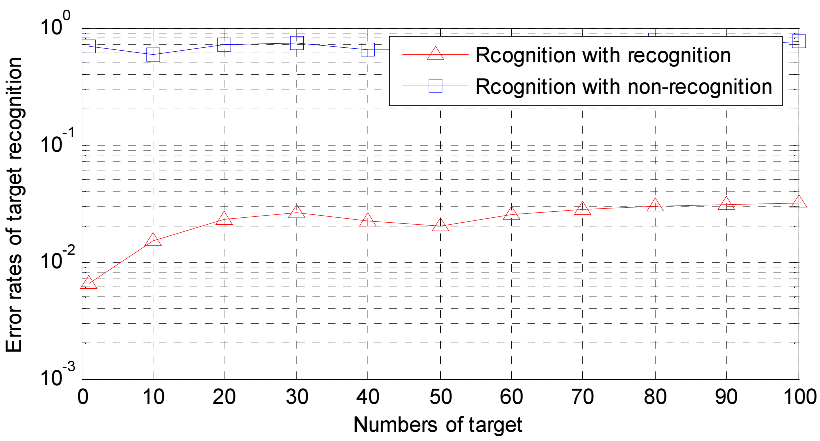

Figure 8. Recognition with attribute blind reduction

✧ Recognition with Importance Degree

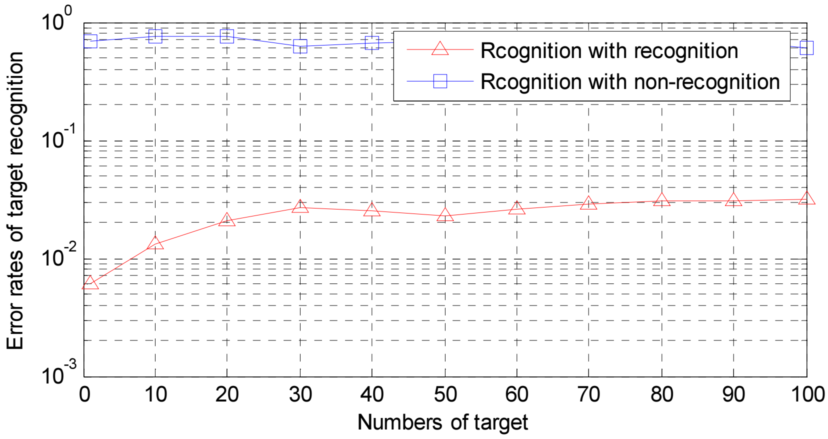

Figure 9. Recognition with importance degree reduction

✧ Recognition with Skowron Discernibility Matrix

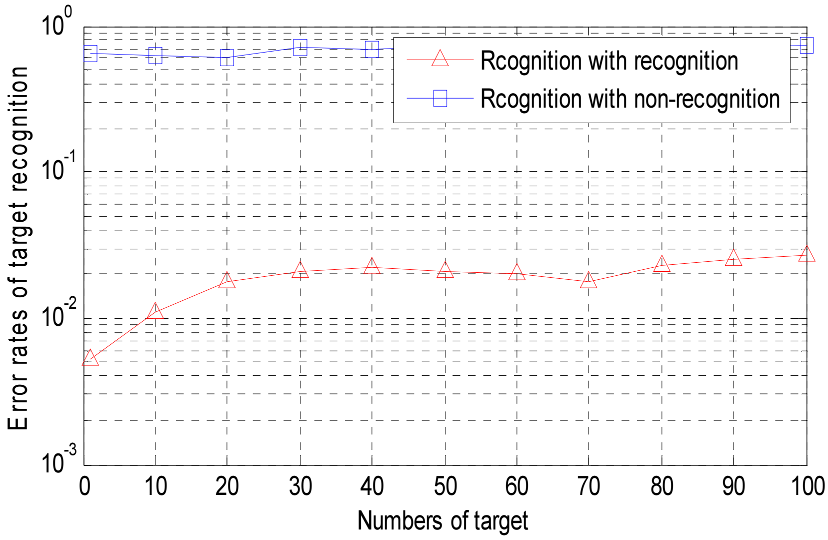

Figure 10. Recognition with Skowron discernibility matrix reduction

V. CONCLUSION

As target recognition has a wide application background in today's information society, how to improve the accuracy of target recognition has been a hot spot research problem. In this paper we aim at introducing the rough set theory in the field of computer to target recognition, so as to simplify the description of target with multi-source information by rough set theory, and to improve the accuracy of recognition.

In this paper, we mainly have completed the following research contents: First, we studied the the background of target recognition, introduced the research status and challenges, discussed the relationship between rough set theory and recognition with multi-information, and proposed a new model for target recognition based on rough set. Then, we made a detailed introduction of the basic theories that used in this paper, including attribute mathematics and rough set theory. And we proposed the mathematical description of target recognition model and the corresponding examples, which contains the binary model, collaborative multi-value model, and collaborative multi-attributes model. Then, we focused on the recognition algorithm used in cooperative target recognition model, including attribute reduction with blind deleting, reduction based on importance degree, and Reduction based on Skowron discernibility matrix. At last, for the the structure of the collaborative target recognition model based on rough set theory, we test the algorithms in VC++ software environment through additive white Gaussian noise channel. Through the simulation comparisons, we found that the algorithm with rough set theory can improve the accuracy of target recognition, and moreover we researched the effect of target numbers on recognition performance, which showed that the error rate is obvious lower when the target numbers are less than 20.

However, there are still some problems that need further research:(1) The data used in simulation is totally generated in a random way, which caused the randomness of simulation results. Therefore, the methods of improving the robustness of the algorithm need to be solved in the future.(2) In this paper, we mainly focused on single target recognition with multi-source information, but in the reality environment, the recognition process is often happed in a group of targets. So, to research the correlation information between different targets may help us improve the recognition results.(3) The increased numbers of description of target attribute will increase the signal transmission energy, which also demands for higher performance of hardware of recognition system. Moreover, in order to exchange more real-time information will take up more channel resources. How to deal with this contradiction will be an important problem.

VI. REFERENCES

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