

# Performance Analysis of Information Fusion Method based on Bell Function

Meiyu Wang<sup>a</sup>, Zhigang Li<sup>a</sup>, Dongmei Huang<sup>b</sup>, and Xinghao Guo<sup>a,\*</sup>

<sup>a</sup>College of Information and Communication Engineering, Harbin Engineering University, Harbin, 150001, China

<sup>b</sup>Electrical engineering school of Harbin Vocational and Technical College, Harbin Vocational and Technical College, Harbin, 150081, China

---

## Abstract

Multi-node and multi-feature fusion is an important approach for digital modulations signal recognition in modern communication field. Information obtained from multi-node and multi-feature needs to be fused because of incompleteness of single feature and uncertainty of single node. As a powerful method for data fusion and conclusion reasoning in uncertain environments, evidence theory is widely used. Establishing reliable BPA is the prerequisite for evidence fusion. In this paper, in order to improve the coincidence of basic probability assignment (BPA) with real probability, the notion of bell function (Bell-F) based similarity evaluation model (SEM) is introduced. Through comparative experiments, it is proved that the new method based on Bell-F is effective for BPA acquisition. Furthermore, a new information fused based digital signal modulation recognition scheme is described. Finally, a case study is given to illustrate the performance of the proposed model. Through test and calculations under the digital modulation signal data set, under 0 ~ 10dB, the recognition rate based on the Bell-F fusion method is above 90%, which is 20% higher than methods without fusion. Under 0dB or less, the integrated recognition rate of the Bell-F is 40% higher than the Gray relation method.

**Keywords:** evidence theory; basic probability assignment function; information fusion; bell function

(Submitted on January 4, 2018; Revised on February 17, 2018; Accepted on March 26, 2018)

© 2018 Totem Publisher, Inc. All rights reserved.

---

## 1. Introduction

Nowadays signal modulation recognition technology, a significant branch of signal analysis, has a great evolutive in the rapid development of information industry; when receiving a signal shorts of prior knowledge, final modulation signals will correctly be recognized by signal treatment [6,10]. Information obtained from multi-node and multi-feature needs to be fused because of incompleteness of single feature and uncertainty of single node. As a powerful method for data fusion and conclusion reasoning in uncertain environments, evidence theory is widely used in information fusion and cognitive decision-making fields [11,17,18,19], as well as digital signal modulation recognition. It not only guarantees the stability of reliability distribution, but also ensures the flexible and efficient data processing. In the practical application of theory, how to perform BPA is the primary problem [14,20]. Compared with the artificial assignment method, it shows many advantages and is gradually becoming the research focus of scholars.

The overall BPA generation can be divided into two types of models: one is that the system automatically generates BPA based on some known conditions; another is based on experts' subjective experience. When using fuzzy theory to describe the target, the model can be divided into two categories: nonlinear and linear. The accuracy of non-linear model description is high. According to different scenarios, researchers have proposed some typical applications and improved algorithms. In recent years, with the rapid development of pattern recognition and artificial intelligence [12], the machine system realizes the autonomous generation of basic probability assignment (BPA) by combining with the evidence theory. To some extent, it is generally true that people cannot guarantee subjective opinions of experts non-confrontational.

---

\* Corresponding author.

E-mail address: 15846758596@163.com

Therefore, the method of setting BPA independently by multiple experts often presents highly conflicting situations [21,22]. The domestic research on this aspect focuses on the application to solve practical problems. Professor Han proposed a method for determining BPA under the principle of maximum entropy in the literature [8], which indicates that the leadership team in the field of domestic information fusion began to pay attention to the importance of BPA generation. In the literature [4], assisted with the theory of random sets, the method of generating BPA by fuzzy sensors is studied and the fusion method based on evidence distance is introduced. Meanwhile, Deng Yong et al. put forward a method founded on gyration radius to obtain similarity, and then obtained the basic probability assignment [3]. In 2012, Kang Bingyi et al. analyzed the advantage of the interval number in describing the target attribute, and a method based on the Crisp Interval distance to generate the BPA is bring forward [9]. Cui Jiaxuan and others used the normal cloud model to generate basic probability assignments [1]. Gong Pengwei proposed a multi-sensor information fusion road condition recognition method combining support vector machine (SVM) and Dempster-Shafer (DS) evidence theory [5]. Zhang Weihua et al. presented a method for calculating the basic reliability distribution of transformer fault based on spatial interpolation [25]. Hongming Mo et al. introduced a new method to measure the distance between two BPAs [15].

This paper will be structured as follows: Section 2 introduces the basic principle of evidence theory and exposes the issues of the fusion formula. In addition, an improved Evidence fusion algorithm based on Euclidean distance is mentioned;. Section 3 discusses the Bell-F based similarity determination method; Section 4 describes our approach and employs meaningful examples to explain each step of Bell-F to generate BPA; Section 5 shows how applying a Bell-F based approach yields meaningful advantages over the old approach. Finally, we conclude that a bell function is used as a method for constructing similarity assessment model (SEM). Through the recognition experiment of communication signal modulation method, the result proves that this method can effectively deal with some important issues of BPA generation and build higher credibility. When the model is known and applied to non-deterministic environments, the SEM shows better adaptability and maintains a higher level of recognition.

## 2. Basic principles of evidence fusion

The structure of the belief function in the evidence theory corresponds to the Bayesian probability model. Therefore, the evidence theory is regarded as an imprecise extension of classical probability theory and Bayesian theory [2,16]. Because it can handle uncertainties caused by inaccurate information, uncertainties information and unknown information, it has a weaker axiom system than probability theory and a more rigorous reasoning process. Thus, evidence theory has been widely used in many fields.

The Evidence Theory first defines a non-empty finite set  $\Theta$  with  $M$  exclusive and exhaustive propositions. We call  $\Theta$  the recognition framework.  $\Theta = \{A_1, A_2, \dots, A_M\}$ , where  $M$  is the total number of propositions in the recognition framework and  $A_i (i = 1, 2, \dots, M)$  represents the  $i$ -th proposition of the recognition framework. A subset of the recognition framework belongs to its power set, expressed as  $2^\Theta$ :

$$2^\Theta = \{\emptyset, H_1, H_2, \dots, H_M, \{H_1, H_2\}, \{H_1, H_3\}, \dots, \{H_1, H_M\}, \dots, \{H_1, H_2, \dots, H_M\}\} \quad (1)$$

Where  $\emptyset$  is represented as an empty set.

Assume that  $\Theta$  is a complete set and  $A$  is a subset of  $\Theta$ . If function  $m: 2^\Theta \rightarrow [0, 1]$  satisfies the following conditions:

$$m(\emptyset) = 0; \sum_{A \in \Theta} m(A) = 1 \quad (2)$$

Where  $m(A)$  is called the basic probability assignment function of proposition  $A$  on  $\Theta$ . It is also called Basic Belief Assignment Function. It describes the degree of evidence support for proposition  $A$ . If  $m(A) > 0$ ,  $A$  will be called coke element.

Suppose that in the same recognition frame  $\Theta$ , the  $N$  evidence bodies after multi-sensor acquisition and processing are  $m_1, m_2, \dots, m_N$  and the focal elements are  $A_1, A_2, \dots, A_M$  respectively, and the evidence bodies are not completely in conflict and independent, then the fusion rule of  $N$  evidence bodies can be used Equation (3) indicates.

$$m(A) = \begin{cases} \frac{1}{1-K} \sum_{\cap A_i = A} \prod_{1 \leq k \leq N} m_k(A_i) & A \neq \emptyset \\ 0 & A = \emptyset \end{cases} \quad (3)$$

When synthesizing two sets of evidence bodies, it indicates the conflicting factors that are generated in the synthesis process, and the definition of conflicting factors is given in Equation (4).

$$K = \sum_{\cap A_i = A} \prod_{1 \leq k \leq N} m_k(A_i) \quad (4)$$

There are unavoidable disadvantages in the conventional method of D-S evidence theory. When the conflict coefficient  $K$  is close to 1, the denominator in the evidence fusion formula loses its meaning. In other words, with high conflict evidence fusion using the conventional method, the result will be counter-intuitive [7,23]. To solve this problem, a method of evidence fusion based on Euclidean distance has been introduced.

Based on the Euclidean distance evidence fusion method, the correlation coefficient between the evidences is calculated by calculating the distance between the two evidences. Then, the original evidence body is weighted by the correlation coefficient, so that a new evidence body is obtained. Finally, the fusion result is produced through the formula (3). The specific algorithm steps are as follows:

---

Algorithm: Euclidean distance-based evidence fusion method

---

Input: Original BPA Evidence Matrix  $\mathbf{M}_{\text{BPA}}$ .

$$\mathbf{M}_{\text{BPA}} = \begin{bmatrix} m_1(A_1) & m_1(A_2) & \dots & m_1(A_q) \\ m_2(A_1) & m_2(A_2) & \dots & m_2(A_q) \\ \dots & \dots & \dots & \dots \\ m_p(A_1) & m_p(A_2) & \dots & m_p(A_q) \end{bmatrix} \quad (5)$$

Output: Algorithm fusion result  $m$ .

1. Calculate the size of the matrix and  $p$  represent the number of rows in the matrix, then the number of columns in the matrix is  $q$ .

2. for  $i = 1 : p$

for  $j = 1 : q$  do

Calculate the Euclidean distance  $d_{ij}$  between every two rows of the matrix and get the distance matrix  $\mathbf{D}$ .

$$d_{ij} = d(m_i, m_j) = \left( \sum_{k=1}^q |m_i(A_k) - m_j(A_k)|^2 \right)^{1/2} \quad (6)$$

3. Calculate the negative exponent of  $e$  for each element in the matrix  $\mathbf{D}$  and obtain  $\text{sim}_{ij}$  to obtain a similarity matrix  $\mathbf{SIM}$ .

$$\text{sim}(m_i, m_j) = e^{-d_{ij}} \quad (7)$$

4. Calculate the row sum of the similarity matrix  $\mathbf{SIM}$  and normalize to obtain the weight coefficient  $\omega_i$ .

$$\text{sup}(m_i) = \sum_{j=1, j \neq i}^q \text{sim}(m_i, m_j) \quad (8)$$

$$\omega_i = \frac{\text{sup}(m_i)}{\sum_{i=1}^p \text{sup}(m_i)} \quad (9)$$

5. The weight vector  $\omega$  performs matrix multiplication with the original matrix  $\mathbf{M}_{\text{BPA}}$  to obtain the row vector  $M$ .

$$m'(A_k) = \sum_{i=1}^N w_i m_i(A_k) \quad k = 1, 2, \dots, M \quad (10)$$

6. Expand the row vector  $M$  into a matrix of  $p$  rows and  $q$  columns to obtain a new BPA matrix  $\mathbf{M}'_{\text{BPA}}$ .

7. Apply D-S evidence synthesis formula to fuse the new BPA and get the fusion results  $m$ .

8. End.

There is a typical example given by Zadeh [24] to describe the disadvantage of conventional D-S method. Next, an experiment is carried out to prove the effectiveness of the Euclidean distance method to solve the conflict evidences. Let  $\Theta = \{A, B, C\}$  or  $\Theta = \{A, B\}$  be a frame of discernment. A decision system has collected three bodies of evidence and the corresponding fusion result shows as Table 1.

Table 1. Examples of high conflict evidences

	Example 1	Example 2	Example 3
$m_1$	$\begin{bmatrix} A & B & C \\ 0.9 & 0.1 & 0 \end{bmatrix}$	$\begin{bmatrix} A & B \\ 0.9 & 0.1 \end{bmatrix}$	$\begin{bmatrix} A & B \\ 0 & 1 \end{bmatrix}$
$m_2$	$\begin{bmatrix} 0 & 0.1 & 0.9 \\ 0.75 & 0.15 & 0.1 \end{bmatrix}$	$\begin{bmatrix} 0.8 & 0.2 \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 \\ 0.9 & 0.1 \end{bmatrix}$
$m_3$			
D-S	$\begin{bmatrix} A & B & C \\ 0 & 1 & 0 \end{bmatrix}$	$\begin{bmatrix} A & B \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} A & B \\ NaN & NaN \end{bmatrix}$
Eu-distance	$\begin{bmatrix} A & B & C \\ 0.9505 & 0.0061 & 0.0434 \end{bmatrix}$	$\begin{bmatrix} A & B \\ 0.8998 & 0.1002 \end{bmatrix}$	$\begin{bmatrix} A & B \\ 0.9743 & 0.0257 \end{bmatrix}$

From Table 1, we know that Dempster rule fails to combine the evidences with high conflict owing to their illogical results. However, the fusion method based on Euclidean distance have high recognition precision of actual target, which is a perfect result to some extent.

The histograms of Figure 1 show the superiority of the method of evidence fusion based on the Euclidean distance. In the above 3 examples, the support degree of the Euclidean distance method to A can reach  $\geq 0.9$ .

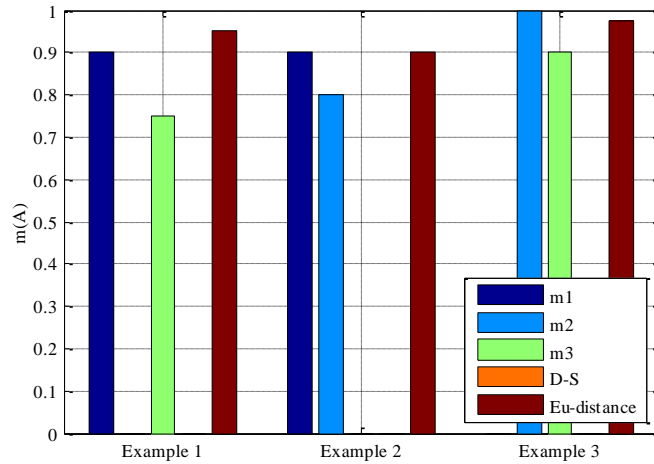


Figure 1. Fusion results of high conflict evidences

### 3. Bell-F-based similarity determination method

The bell-shaped curve is very common. The normal distribution we are familiar with is a kind of bell-shaped curve. It is a bell-shaped curve with a middle height and gradually falling at both ends and completely symmetrical. A function that uses parameters to adjust the shape of the bell curve is called a bell function. This section will introduce a Bell-F as a foundation for SEM [13] based on general cognitive rules.

### 3.1. Bell Function

Bell-F is introduced in this paper to describe the cognitive target attributes. The function expression is:

$$f(x) = \frac{w}{1 + \left(\frac{x-c}{a}\right)^{2b}} \quad (11)$$

As shown in Figure 1, Bell-F is determined by the parameters  $a$ ,  $b$ ,  $c$  and  $w$ . The maximum membership value  $w$  is obtained at  $c$ .  $w/2$  is taken at  $c-a$  and  $c+a$ , and  $b$  can control the shape of the curve.  $w$  is the maximum membership value, and the value range is  $[0,1]$ . This paper defines  $w=1$ .

In the curve of Figure 2,  $c$  is the function of the center point (CP), and the change of membership in the vicinity of  $c$  is gentle. In the process of cognition, the distance to the target attribute CP turns closer, the affirmation of the target is stronger and  $S$  is the bigger. The length of interval  $[c-a, c+a]$  is controlled by  $a$ . When  $S=0.5$  is regarded as the decision threshold and  $a$  is the one-way decision length,  $c-a$  and  $c+a$  will be the decision points (JP), and the membership degree near JP is the most steep. The curve will gradually turn "tighten" as  $b$  increases, and the change around CP will be gentler. At the same time, the change near JP will be steeper. This indicates that as the degree of cognition gradually deepens, the cognitive characteristics get enhance.

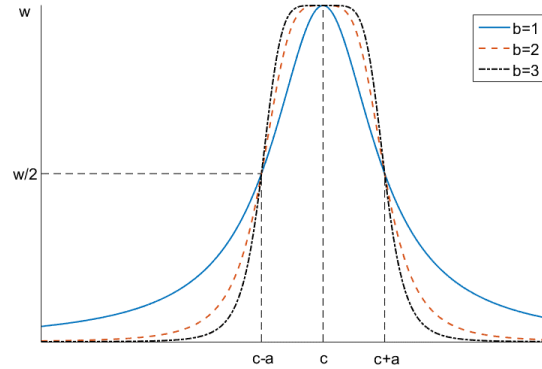


Figure 2. Bell-F curve and key points

Figure 2 shows that Bell-F describes many features of cognitive rules and constructs SEMs in a fine-grained manner, which solves the problems that the linear model has the defects of cognitive description process and cannot meet the modeling requirements.

### 3.2. SEM construction

Assume that there are  $m$  cognitive goals

$$\Theta = \{C_1, C_2, \dots, C_m\} \quad (12)$$

There are  $n$  cognitive evidence (that is, the target attribute), the value is limited to a single point real number

$$A = \{A_1, A_2, \dots, A_n\} \quad (13)$$

Type  $i$  corresponding to the attribute  $j$  is recorded as  $A_j^{c_i}, i \in [1, m]$  and  $j \in [1, n]$ ;

Then, the SEM of attribute  $j$  is

$$model_j = \{A_j^{c_1}, A_j^{c_2}, \dots, A_j^{c_m}\} \quad j \in [1, n] \quad (14)$$

According to the known samples, the eigenvalues were extracted: mean  $\xi$ , standard deviation  $D_{std}$ , maximum difference  $D_{max}$  and number of samples  $N$ , and the SEM was constructed as shown in Figure 3.

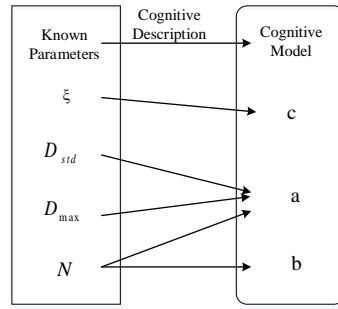


Figure 3. Bell-F to build the concept map

The known parameters were passed through the cognitive description process to determine Bell-F parameters for each target property in the SEM.

Definition 1. Unidirectional decision length  $a$

$$a = \begin{cases} D_{std} + \frac{D_{max} - D_{std}}{2} \times \frac{N}{N_{sa}}, & N \leq N_{ta} \\ D_{std} + \frac{D_{max} - D_{std}}{2}, & N > N_{ta} \end{cases} \quad (15)$$

The parameter determines the corresponding abscissa position of the Bell-F whose function value is  $w/2$ , which in turn determines the degree of concentration of the Bell-F, that is, the "fat and thin" bell-shaped function.  $N$  is the number of samples and  $N_{ta}$  is the threshold for the number of samples to reach  $N$ . It can be determined according to the sample size experienced by the transfer from standard deviation (cognitive initial state) to the maximum difference (cognition mature state) in the application scenario.

Definition 2. Determination of strength  $b$

$$b = \begin{cases} \frac{N}{N_{tb}} + 1, & N \leq N_{tb} \\ 2, & N > N_{tb} \end{cases} \quad (16)$$

The parameter  $b$  also affects the degree of concentration of the bell-shaped function. The minimum value is set to 1, and  $N$  is the number of samples. It is the number threshold when the cognitive status reaches the maximum decision strength, which depends on the degree of cognitive difficulty. Difficult scenarios require more known quantities to increase "confidence" and therefore increase; and vice versa.

Definition 3. Center point  $c$

$$c = \xi \quad (17)$$

$c$  is the central position of the target attribute, and the bell-shaped function value (S) has a maximum value of 1.

#### 4. A new method of BPA generation

Based on the previous section, this section proposes a new BPA generation method. The detailed steps are as follows:

Step 1. Extract all the target evidence information from the known samples, and build bell function models based on Bell-F about various attributes

- Step 2. Use the principle of maximum membership to determine the similarity between NI and each target  
 Step 3. Compute the target union similarity  $S$   
 Step 4. Regularize all  $S$  to generate BPA

Based on the above steps, BPA generation algorithm flow can be seen in Figure 4.

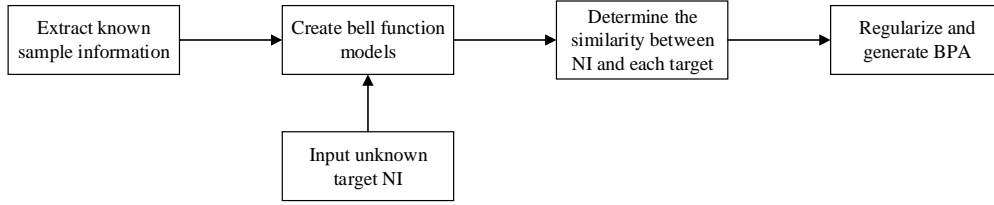


Figure 4. BPA generation algorithm flow

The following specific examples of digital modulation recognition are used to illustrate the effectiveness of the new method. The data set for building the bell function model consists of 27,360 signals. The signal types are divided into 9 types. The signal-to-noise ratio range is -5dB to 10dB. The number of each signal at a certain signal-to-noise ratio is  $N = 190$ . A signal contains 7 different entropy features (respectively: WVD time domain transform RenYi entropy, wavelet energy spectrum entropy, power spectrum Shannon entropy, power spectrum index entropy, singular spectrum Shannon entropy, singular spectrum index entropy, and bispectrum entropy). The cognitive domain has 9 major goals: 2ASK, 4ASK, 2FSK, 4FSK, 8FSK, BPSK, QPSK, 16QAM, and 32QAM. Nine large targets are further divided into 26 small targets; the total number of samples is 27360, with 190 targets per target.

Taking the four-signal-to-noise ratio WrD temporal RenYi entropy of WVD as an example, the detailed process of generating evidence BPA by RenYi entropy is deduced.

Step 1. Create Attribute SEM. According to the cognitive application scenario, the SEM scene parameters are determined. In this paper, the values of  $N_{ta} = 800$  and  $N_{tb} = 300$ , and the range of  $b$  is  $[1, 2]$ . The characteristic information of RenYi entropy is extracted from the sample, and the bell-type parameter is obtained by entering the formula, as shown in Table 2.

Step 2. As shown in Figure 5, take a sample of data  $NI_x$  to find the similarity  $S$ . Enter the model evaluation to determine the result and take the properties  $A_1 = 6.2$  of  $NI_x = (A_1 = 6.2, A_2 = 2.2, A_3 = 4.5, A_4 = 1.5)$ . The Step2 single set of results and the goal of combining the results shown in Table 3.

Step 3. Calculate  $S$  according to equation.

Step 4. Regularization process generates BPA, as shown in Table 4.

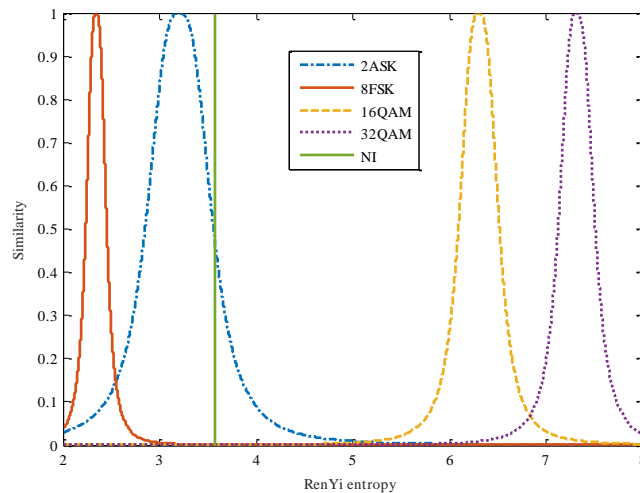


Figure 5. Determines the similarity between NI and each model

Table 2. Attributes RenYi entropy feature information and its corresponding parameters

	$\xi$	$D_{std}$	$D_{max}$	N	a	b	c
2ASK	3.2052	0.3123	0.8360	190	0.4825	1.7500	3.2052
8FSK	2.3452	0.0941	0.2867	190	0.1567	1.7500	2.3452
16QAM	6.3057	0.1815	0.5743	190	0.3091	1.7500	6.3057
32QAM	7.3179	0.1689	0.4726	190	0.2675	1.7500	7.3179

Table 3. Similarity results

Signal type	2ASK	8FSK	16QAM	32QAM
Similarity	0.4243	0.0009	0.0006	0.0002

Table 4. BPA by attribute RenYi entropy

Signal type	2ASK	8FSK	16QAM	32QAM
Similarity	0.9960	0.0021	0.0014	0.0009

## 5. Experiments and results analysis

This section will conduct two comprehensive experiments to obtain experimental results and statistically identify the correct rate.

### Experiment 1: Verify the effectiveness of the BPA acquisition method

In order to verify the validity of the new BPA method, Experiment 1 simply determines the recognition rate based on the obtained BPA and does not perform the fusion of multi-node and multi-features. Taking RenYi entropy as an example, the data set for building the Bell-F model consists of 27,360 signals. The signal types are divided into 9 types. The signal-to-noise ratio range is -5dB to 10dB. The number of each signal at a certain signal-to-noise ratio is  $N = 190$ .

Specific steps are as follows:

Step 1. Randomly select 9 signal target samples of 130, a total of 18720 signals as a training sample set. Use the remaining 8640 signal samples as a test set.

Step 2. Construct the template of 9 kinds of signals in 16 signals to noise ratio, classify the remaining unknown samples, and use this method to generate the evidence BPA of RenYi entropy.

Step 3. Apply the comprehensive recognition rate of RenYi attribute BPA.

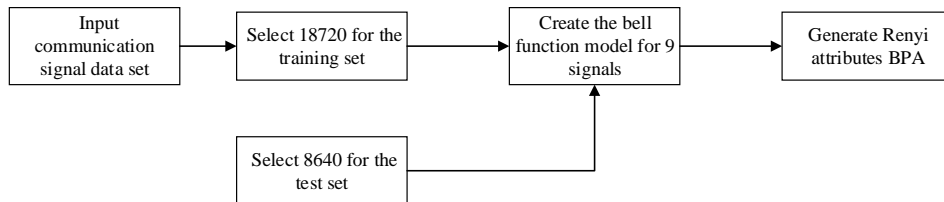


Figure 6. Procedure and steps of recognition rate based on the BPA

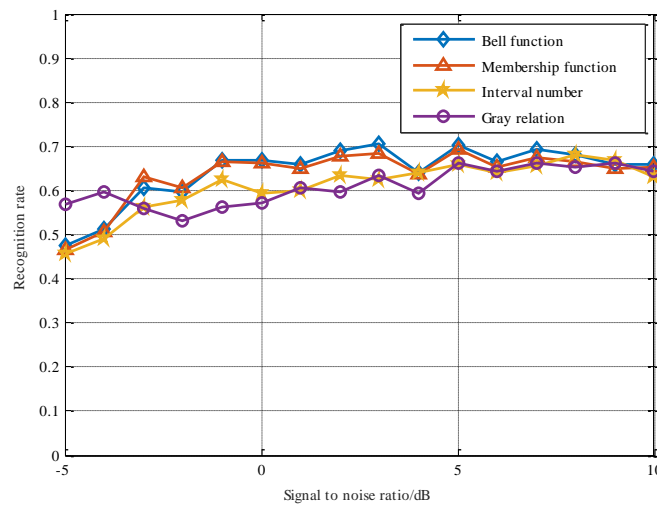


Figure 7. Comparison of the results of the four methods



The recognition rate of different BPA acquisition methods is shown in Figure 7. It can be seen that the Bell-F method is superior to the other three methods. Under 0dB, recognition rate of Bell-F reaches 67%, nearly 10% higher than the Grey relation method. The result shows that the recognition rate of BPA obtained by Bell-F has reached 70% before it is fused, which illustrates the BPA acquisition method based on Bell-F is very effective.

## Experiment 2: Verify the superiority of the evidence fusion method

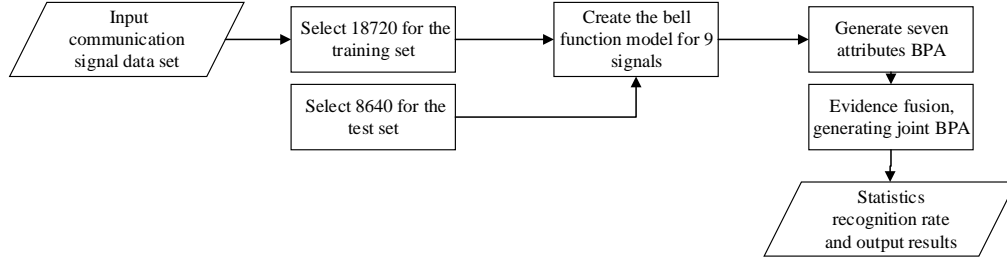


Figure 8. Experimental procedure and steps

Specific steps are as follows:

Step 1. Randomly select 9 signal target samples of 130, a total of 18720 signals as a training sample set. Use the remaining 8640 signal samples as a test set.

Step 2. Construct the template of 9 kinds of signals in 16 signals to noise ratio, classify the remaining unknown samples, and use this method to generate the evidence BPA of each attribute.

Step 3. Apply the evidence of each attribute BPA.

Step 4. Employ the Euclidean distance-based evidence fusion method to generate a joint BPA and check the accuracy

In accordance with the above process, the bell-shaped function is established until BPA is generated, and after multiple evidence combinations by using Euclidean distance-based evidence fusion method, the final joint BPA is obtained.

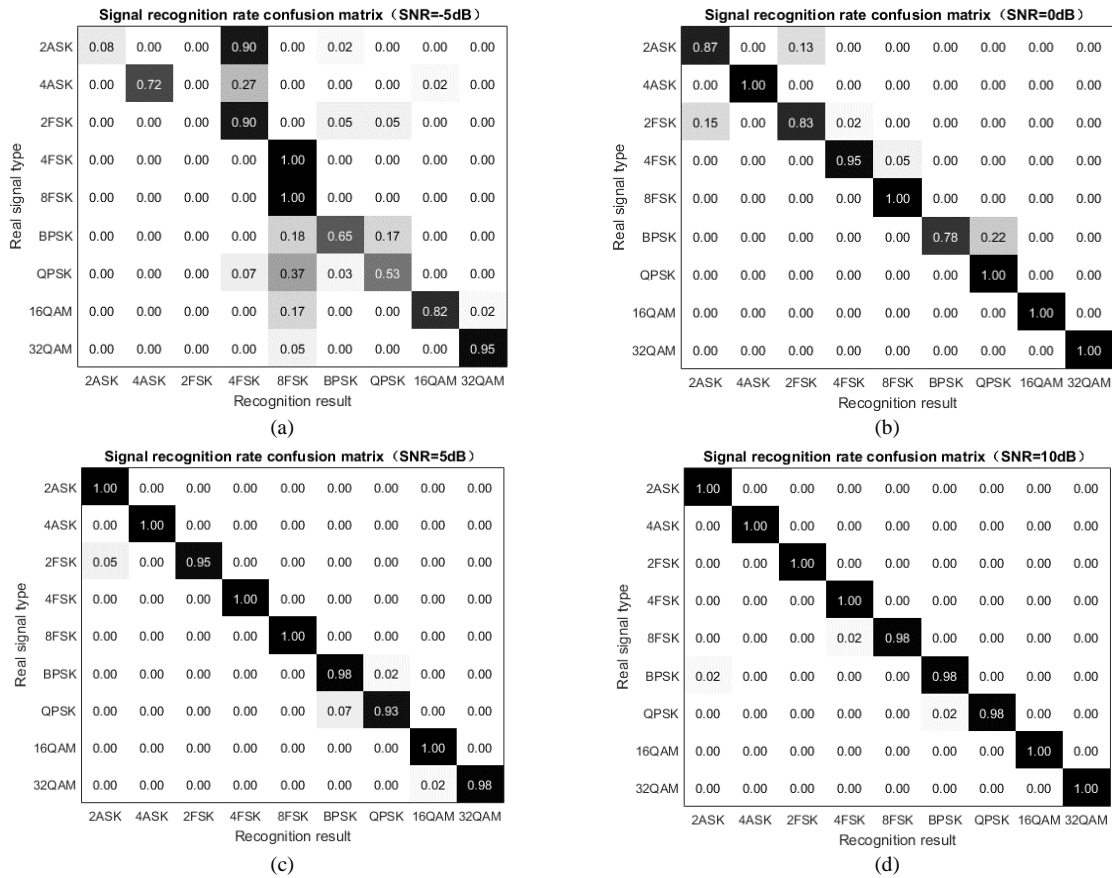


Figure 9. (a) obfuscation matrix of -5dB (b) obfuscation matrix of 0dB (c) obfuscation matrix of 5dB (d) obfuscation matrix of 10dB

Figure 9 shows the recognition rate of digital modulation signals under -5dB, 0dB, 5dB and 10dB, respectively in the following obfuscation matrix. In (a), most of the 2ASK signals are misidentified as 4FSK signals, and most of the 4FSK signals are mistaken for 8FSK. The reason for this phenomenon is that in the case of low signal to noise ratio (-5dB), the characteristics of 2ASK, 4FSK and 8FSK are similar, and the overlapped BPA is generated. In (b), every kind of signal can be correctly and basically identified. In (c) and (d), in the case of 5dB and 10dB, the diagonal element in the obfuscation matrix is nearly 1, indicating that the recognition effect is basically 100% at this case.

The recognition rates of fusion based on 4 different BPA acquisition methods (Grey relation, Interval number, Membership function and Bell function) at -5dB, 0dB, 5dB and 10dB are shown in Table 5.

Table 5. BPA of fusion results of different methods

BPA acquisition method	-5dB	0dB	5dB	10dB
Grey relation	0.1203	0.4185	0.9796	0.9998
Interval number	0.4370	0.4944	0.9463	0.9963
Membership function	0.6111	0.9056	0.9852	0.9981
Bell function	0.5278	0.9370	0.9833	0.9944

Table 5 shows that when the SNR is 10 dB, the recognition rate of Bell-F slightly reduces. The reason for this phenomenon is that the characteristics of the signal are relatively uniform under high signal-to-noise ratio. The model of the Bell-F constructed for different signals is almost overlapped, which cannot distinguish the signal type.

The recognition rate for directly recognizing the modulated signal after BPA acquisition is lower in Figure 7. According to the flow in Figure 8, for evidence fusion and four BPA acquisition methods, a fusion scheme based on the Euclidean distance is applied to obtain the recognition rate curves in Figure 10. Figure 10 shows a comparison of fusion recognition effects based on the three classic BPA generation methods with the Bell-F in this paper.

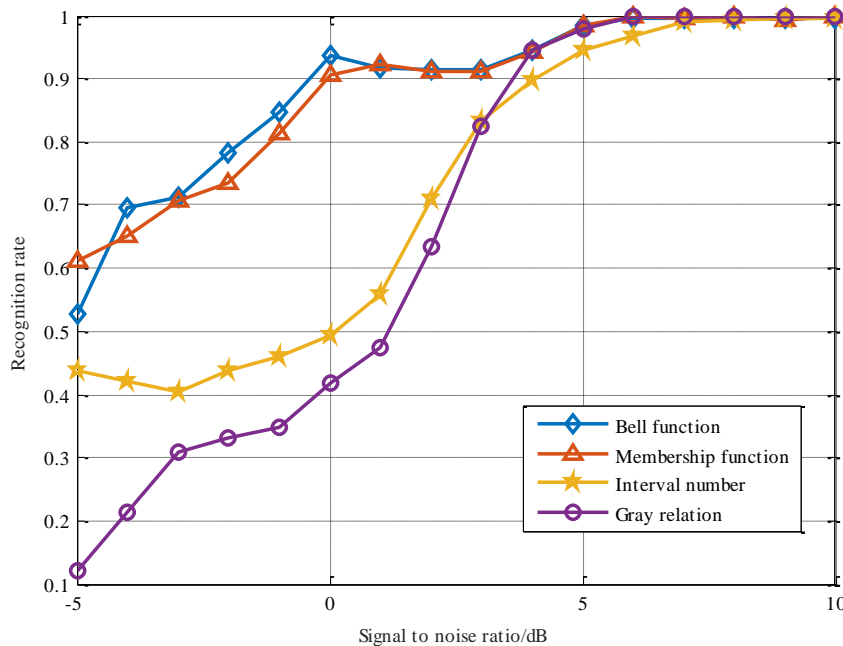


Figure 10. Comparison of the results of the four methods

In Figure 10, in the case of low SNR, for example, SNR = 0 ~ 5dB, only the bell function and membership function are identified to be higher than 50%. Under 0 ~ 10dB, the recognition rate based on the Bell-F fusion method is above 90%. Under 0dB or less, the integrated recognition rate of the Bell-F is 40% higher than the Gray relation method. Comparing Figure 7 and Figure 10, the recognition rate based on the Bell-F fusion method is 20% higher than methods without fusion that means fusion methods have greatly improved the recognition rate.

The above experiments show that when  $N$  ensures a certain scale, and the Bell-F based fusion method can give more reliable confidence support. The recognition results of the other two methods are not ideal. When the SNR is greater than

0dB, the recognition rate of the bell function and the membership function can reach about 90%; when the SNR is greater than 6dB, the recognition rate of the four methods is close to 100%. In general, the recognition rates of the bell function and the membership function are similar, but the method of generating the BPA by the membership function has a "zero paradox". In the process of evidence fusion, it is easy to cause errors, and the bell function is on both sides of the function. The tailings in the Bell-F effectively overcome the "zero paradox" phenomenon. There is also a recognition rate of no less than 50% at a low signal-to-noise ratio. It shows that the bell function has a good ability to adapt to non-deterministic environments.

## 6. Conclusions

For the sake of improving the recognition rate of digital signal modulation recognition, a BPA generation algorithm based on Bell-F is proposed in this paper. BPA acquisition is a prerequisite for the application of evidence theory to signal modulation recognition. The Bell function can guarantee the stability of reliable allocation in the aspects of SEM construction and BPA generation. This paper carries out the identification of evidence fusion based on Bell-F through converting the feature of digital signal to BPA. The experimental results have concluded that the algorithm has a reliable effect on the modulation signal recognition and a better recognition rate. Fusion methods have greatly improved the recognition rate than methods without fusion. The recognition rate based on the Bell-F fusion method is above 90% under 0~10dB, and under 0dB or less, the integrated recognition rate of the Bell-F is 40% higher than the Gray relation method. The further work is that for some cases where the normality of the target attribute is insufficient, it is necessary to perform normalization conversion before BPA generation. For different application environments, such as multi-feature signal recognition, the determination of each scene parameter needs more exploration.

## Acknowledgements

This paper is funded by the International Exchange Program of Harbin Engineering University for Innovation-oriented Talents Cultivation. Meantime, all the authors declare that there is no conflict of interests regarding the publication of this article. We gratefully thank the reviewers for their very useful discussions.

## References

1. J. X. Cui, B. Li, and Y. C. Li, "Generation method and application of basic probability assignment based on normal cloud model[J]," *Journal of Data Acquisition and Processing*, 2015, 30(06):1318-1324. (in Chinese)
2. A. P. Dempster, "Upper and lower probabilities induced by a multivalued mapping," *The annals of mathematical statistics* (1967): 325-339
3. Y. Deng, W. Jiang, and X. Xu, et al, "Determining BPA under uncertainty environments and its application in data fusion [J]," *Journal of Electronics (China)*, 2009, 26(1):13-17
4. Y. Deng, W. K. Shi, and Z. F. Zhu, et al, "Combining belief functions based on distance of evidence[J]," *Decision Support Systems*, 2004, 38(3):489 -493
5. P. W. Gong, Y. Q. Fei, and L. B. Song, "Traffic-recognition method of hybrid mobile robot based on multi-sensor information fusion[J]," *Journal of Shanghai Jiao Tong University*, 2017, 51(04):398-402. (in Chinese)
6. Y.B. Gu, and M.L. Yang, "Research on OFDM and the Single Carrier Signal Modulation Recognition," *Instrumentation and Measurement, Computer, Communication and Control (IMCCC)*, 2015 Fifth International Conference on. IEEE, 2015:1245-1249
7. D. H. Han, et al, "New dissimilarity measures in evidence theory[C]," *Information Fusion (FUSION)*, 2011 Proceedings of the 14th International Conference on, IEEE, 2011: 1-7
8. C. Z. Han, D. Q. Han, and J. Jie, "From biological cognition and perception to methodologies of system engineering [J]," *Systems Engineering-Theory & Practice*, 2008 (supplement):75 -93. (in Chinese)
9. B. Y. Kang, Y. Li, Y. Deng, Y. J. Zhang, and X. Y. Deng, "Basic probability assignment generation method based on interval number and its application[J]," *Acta Electronica Sinica*, 2012, 40(06):1092-1096. (in Chinese)
10. H. L. P. Kumar, and S. Lakshmi, "Automatic Digital Modulation Recognition System Using Feature Extraction," *Emerging Trends in Electrical, Communications and Information Technologies*, Springer, Singapore, 201-208, 2017
11. Y. Lin, C. Wang, J. X. Wang, and Z. Dou, "A Novel Dynamic Spectrum Access Framework Based on Reinforcement Learning for Cognitive Radio Sensor Networks[J]," *Sensors*, 2016, 16(10): 1-22
12. Y. Lin, X. Zhu, and Z. Zheng, et al, "The individual identification method of wireless device based on dimensionality reduction and machine learning[J]," *The Journal of Supercomputing*, 2017: 1-18
13. Y. L. Liu, M. Martin, and M. Kraak, "Semantic similarity evaluation model in categorical database generalization," *International Archives of Photogrammetry Remote Sensing And Spatial Information Sciences*, 2002, 34(4): 279-285
14. M. Liu, B. Z. Yuan, and X. F. Tang, "A new approach to determine the similarity parameters in evidence-theoretic k-NN rule[J]," *Acta Electronica Sinica*, 2005, 33(4):766 -768. (in Chinese)

15. H. M. Mo, X. Lu, and Y. Deng, "A generalized evidence distance[J]," *Journal of Systems Engineering and Electronics*, 2016, 27(02): 470-476
16. G. Shafer, "A mathematical theory of evidence," Vol. 42. Princeton university press, 1976
17. J. Sun, W. Wang, and L. Kou, et al, "A data authentication scheme for UAV ad hoc network communication[J]," *The Journal of Supercomputing*, 2017: 1-16
18. H. Wang, L. Guo, and Z. Dou, et al, "A New Method of Cognitive Signal Recognition Based on Hybrid Information Entropy and DS Evidence Theory[J]," *Mobile Networks and Applications*, 2018: 1-9
19. H. Wang, J. Li, and L. Guo, et al, "Fractal Complexity-Based Feature Extraction Algorithm of Communication Signals[J]," *Fractals*, 2017, 25(04): 1740008
20. C. L. Wen, Z. Zhou, and X. B. XU, "A new similarity measure between generalized trapezoidal fuzzy numbers and its application to fault diagnosis[J]," *Acta Electronica Sinica*, 2011, 39(3A): 1 -6. (in Chinese)
21. D. Q. Han, "Multiple classifiers fusion based on weighted evidence combination[A]," *IEEE International Conference on Automation and Logistics [C]*. Jinan, China: IEEE, 2007. 2138 - 2143. (in Chinese)
22. C. L. Wen, D. H. Zhou, Q. Pan., and H. C. Zhang, "Distributed information fusion algorithm for single sensor dynamic system on the basis of multiscale dynamic models [J]," *Acta Automatica Sinica*, 2001, 27(2): 158-165. (in Chinese)
23. C. L. Wen, Z. Zhou, and X. B. XU, "A new similarity measure between generalized trapezoidal fuzzy numbers and its application to fault diagnosis[J]," *Acta Electronica Sinica*, 2011, 39(3A): 1 -6. (in Chinese)
24. L. A. Zadeh, "A simple view of the Dempster-Shafer theory of evidence and its implication for the rule of combination," *AI magazine* 1986, 7(2): 85
25. W. H. Zhang, J. S. Yuan, S. Wang, and L. Zhang, "A Transformer Failure Basic Reliability Allocation Calculation Method Based on Improved Three-ratio Method[J]," *Power System Protection and Control*, 2015, 43(07): 115-121. (in Chinese)