Intelligent Data Fusion Technology for Enterprise Identification Market Customer Demand in Complex Environment

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Abstract: With the advent of the information age, the competition of the global economy has reached unprecedented intensity. In the competition, enterprises use various methods to seek survival and development. In fact, customers are the recipients of enterprise products, the source of enterprise profits, and the foundation of enterprise survival and development. However, due to the fierce competition and the confusion of market customer information, enterprises cannot identify the real needs of market customers. Based on the above background, the purpose of this paper is to study the intelligent data fusion technology of enterprise identifying market customer demand in complex environment. Firstly, according to the existing problems of enterprise identifying market customer demand in complex environment, this paper proposes an intelligent attribute fusion model. The model is implemented by three modules: environment analysis, uncertain information processing and classification and identification information fusion. The environment analysis module directly affects uncertain information processing module and classification information fusion module. In different information levels and processing processes, it solves the problems of environment self, adaptability, robustness and flexibility required by data fusion system in dynamic and changeable environment question. Through the experimental comparison and analysis, the BP neural network algorithm used in this paper achieves 92.73% accuracy rate in identifying market customer demand, and then proves that multi-sensor data fusion can effectively improve the accuracy rate of enterprise identification compared with single sensor from the aspects of single sensor and multi-sensor.

1. Introduction

The company focuses on the needs of customers and combines the resources of the organization to provide products and services to certain target customers. As a guide to the long-term and overall organization of the organization's activities, its strategy must be based on itself and centered on customer needs [1-5]. The environment is changing, the needs of customers are changing, and the organization itself is changing, so the strategy should change accordingly. Organizational strategy is a global guide to the activities of the entire organization. Since all activities of the organization are transferred around the customer, the formulation of the strategy must be centered on the needs of the customer. Otherwise, the formulated strategy will have no guiding significance for the actions of the organization. Therefore, customer demand is the center of the company to develop dynamic strategic management. Customer demand analysis is the premise and basis for strategy formulation. The foothold of all analysis of strategy should be in the customer's demand. Intense competition is forcing companies to constantly seek ways to gain a competitive advantage. The traditional competitive thinking is usually locked in the competition. In order to defeat the competitors, while defeating the opponents, while increasing the market share, it also weakens its own profits. The competitive strategy based on customer demand is not only concerned with competitors. At the same time, it pays more attention to customer needs. It takes innovation as a means to satisfy and create customer needs as the center, and to refer to competitors, so as to meet customer needs in a more effective way and win competitive advantage. The formation of competitive advantage based on customer needs is achieved through the process of “identification of customer needs – satisfaction of customer needs – satisfied customers”. By identifying the various needs of customers, through strategic innovation, technological innovation and management innovation, the company's resource capabilities are used to design and implement a series of competitive strategies to capture and form the ultimate competitive advantage of the company [6-10].

Due to the increasingly fierce competition in enterprises, enterprises will interfere with market information, making the market environment increasingly harsh and more complicated. This complication is manifested by inaccuracies, incompleteness, and unreliability of the data obtained; rapid changes in data and an increase in the amount of data. Due to the complex and ever-changing environment, data fusion technology should have certain adaptability and robustness, not only can adapt to the dynamic changes of the environment, but also reduce the adverse effects of some unknown uncertain factors on the system, so it needs to develop self-learning and adaptive data fusion technology. In addition, data fusion functionally mimics the ability of the human brain to comprehensively address problems. The human brain is the best fusion system. It can effectively and quickly integrate different information in various ways. It has strong learning and self-adaptive ability and is a true intelligent system. The essence of intelligence is that if a system can improve its performance or its ability to maintain an acceptable level in the presence of uncertainty, its main characteristics are learning ability, adaptability, fault tolerance and self-organizational skills. Therefore, the multi-sensor target recognition system needs to be applied in a complex battlefield environment, and it is necessary to develop an intelligent data fusion technology [10-15].

The ability of producers to identify and estimate market demand can affect the success of smallholder marketing. The general problem is that most producers receive unexpectedly low prices when they sell their products. Ma proposed that Rapid Market Assessment (RMA) is a way to collect reliable market information in the short term, which is cheaper than traditional market research. This approach helps to quickly understand complex market relationships and guides producers in making decisions about directing their production to market opportunities [16]. Dongdong proposed a structural health monitoring framework based on hybrid intelligent systems to calculate the composite structural health index as a structural health indicator. Using Dingdong’s proposed health structure monitoring framework, it provides decision-level analysis for structural health monitoring. In contrast, recent research has focused on signal processing, mechanical modeling, and computer-based systems that are not powerful enough to provide decision-level analysis in the face of heterogeneous data sources. Therefore, data fusion techniques are needed to mitigate data conflicts, lacking the possibility of simplicity and imperfections, which are generated by heterogeneous data sources computing composite structural health indices, which is critical for risk analysis. The intelligent data fusion framework proposed by Dongdong is based on hybrid adaptive resonance theory neural network (learned from dynamic data) and adaptive fuzzy inference (high-level reasoning of dynamic fuzzy rules derived from membership functions composed of time-series data) [17]. Liu proposed a correlation vector machine (RVM) based on ant colony optimization algorithm, which is an intelligent multi-sensor data fusion method for gearbox fault detection. RVM is a sparse probability model based on support vector machine (SVM). Compared with SVM, RVM not only has higher detection accuracy, but also has better real-time precision. The ACO algorithm is used to determine the kernel parameters of the RVM. In addition, the original vibration signal is preprocessed using Integrated Empirical Mode Decomposition (EEMD) to eliminate the effects caused by noise and other unrelated signals. The Distance Assessment Technique (DET) is used to select the primary features as inputs to the ACO-RVM, thus eliminating redundancy and inference in a large number of features. Two gearboxes were used to demonstrate the performance of the proposed method. The experimental results show that ACO-RVM has higher fault detection accuracy than normal cross-validation (CV) RVM [18]. The Internet of Things (IoT) has recently received widespread attention and played an important role in the deployment of smart city applications. Many of these smart city applications rely on sensor fusion capabilities from various data sources in the cloud. Wang introduced the concept of the Internet of Things and detailed ten different parameters that control their sensor data fusion assessment framework. They then evaluated the latest technology for sensor data fusion based on their sensor data fusion framework. Wang's main goal is to examine and investigate different sensor data fusion studies based on their assessment framework. Major open research issues related to sensor data fusion are also presented [19]. Multi-sensor data fusion technology plays an important role in practical applications. Carlo proposed a multi-sensor data fusion method based on new evidence confidence measure and confidence entropy. First, a new belief Jensen-Shannon divergence was designed to measure the difference and the degree of conflict between the evidence; then, credibility can be obtained to represent the reliability of the evidence. Next, taking into account the uncertainty of the evidence, the amount of information in the evidence is measured by using belief entropy to measure the relative importance of evidence. Thereafter, the credibility of each evidence is modified by using a quantitative amount of information that will be used to obtain the appropriate weight for each evidence. Finally, the final weight of the evidence is applied to the body of the evidence before using Dumpster’s merger rules. Numerical examples show that the method can effectively deal with contradictory evidence and increase the confidence of the target to 99.05%. In addition, the application in fault diagnosis proves the effectiveness of the proposed method [20].

Firstly, according to the problems existing in identifying market customer demand under the complex environment, this paper proposes a model of intelligent attribute fusion. The model is implemented by three modules: environment analysis, uncertain information processing and classification and identification information fusion. The environment analysis module directly affects uncertain information processing module and classification information fusion module. In different information levels and processing processes, it solves the problems of environment self-adaptability, robustness and flexibility required by data fusion system in dynamic and changeable environment question. Through the experimental comparison and analysis, the BP neural network algorithm used in this paper achieves 92.73% accuracy rate in identifying market customer demand, and then proves that multi-sensor data fusion can effectively improve the accuracy rate of enterprise identification compared with single sensor from the aspects of single sensor and multi-sensor.

2. Proposed Method

2.1 Modeling of Intelligent Attribute Fusion

In a complex environment, intelligent attribute fusion emphasizes the fusion of “full information”. The “full information” here includes the target detection information of the sensor, environmental information, sensor and system working status information, data link and historical data information of other platforms. How to use these diversified information to ensure the accuracy and robustness of the fusion system, while also paying attention to the fusion structure, real-time performance, simple calculation and easy engineering implementation, the first is to establish an effective fusion system model. Due to the dynamic and dynamic environment of complex interference, it is not easy to implement an effective attribute fusion system, especially in the case of data uncertainty and incomplete target prior knowledge base. The intelligent attribute fusion model is divided into three modules: environmental analysis, uncertain information processing and classification and identification information fusion. As shown in Figure 1.

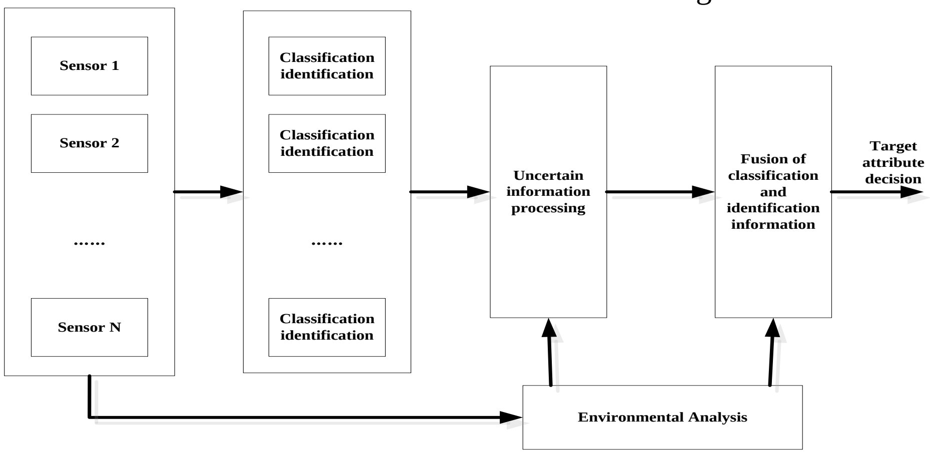

Figure 1: Intelligent attribute fusion model

(1) Environmental analysis

Changes in the work environment directly affect the robustness and reliability of the identification system. At this time, the multi-sensor target recognition system should adopt the corresponding knowledge base and working mode according to the actual environment. Therefore, it is necessary to establish a complete intelligent environment analysis module, which can analyze various indicators of the environment in which the system is located, provide current environment description information and parameters to the fusion system, it can use these information and parameters to further control the operation, management and data fusion mode of the sensor, participate in the processing of uncertain information. For the implementation of this module, in addition to all necessary environmental description information, expert experience and experimental and theoretical analysis are required. Expert system, fuzzy reasoning, neural network and other artificial intelligence methods should be used. At the same time, the module is required to have self adaptability and self-study habits.

(2) Uncertain information processing

Attribute fusion is to comprehensively process some low-level or low-precision sensor target identification information to obtain more accurate and reliable recognition results. It is worth noting that each sensor information usually has different characteristics: real-time or non-real-time, fuzzy or erroneous, mutually supportive or complementary, even contradictory or competitive, and it becomes uncertain because of the influence of various random factors. When these multi-source uncertain information enters the fusion system, the uncertainty factors are also transmitted and influenced by each other, and the fusion results themselves are uncertain. Due to the influence of uncertainty, information conflicts are often introduced in the fusion process. When the advantages of error information increase and the advantages of correct information decrease, the effectiveness of the fusion system will be seriously reduced, and even the final result of the integration is wrong. Especially in dynamic and complex environments, there are many factors affecting the uncertainty of sensor classification and identification information, and the degree of information impact is difficult to determine. At this time, the fusion center must accurately and timely grasp the situation and information of environmental changes. Reliability, choose a reasonable fusion algorithm to ensure that the fusion performance will not be reduced. Therefore, to ensure the reliability and robustness of a multi-sensor fusion system, the key to solving this problem is the combination of the processing of uncertain information and the structure and algorithm of attribute fusion.

However, the uncertainty in the information being fused is itself a polymorphism. Each variant of uncertainty has a different data model, and no one can adapt to all situations. When expressing and processing uncertainty information, it is necessary to carefully study the characteristics of the actual problem and select the appropriate model. According to the different forms of information representation and information uncertainty, the processing of uncertain information should be handled in different aspects and at different levels. For the low-level data information, the processing of the uncertain information is mainly reflected in the correction of the detection error; for the characteristic information of the middle layer, the uncertainty information processing is mainly the reliability analysis of the information and its effective utilization; Determining information processing is the rationality analysis of information, the processing of conflict information, and the screening and reorganization of effective information.

(3) Fusion of classification and identification information

To adapt to the complex environment and the dynamic characteristics of the target time-varying, under the premise of the prior knowledge, to ensure that the system has good robustness and adaptability, the fusion should be flexible, it should have the ability of error detection and multi information processing.

The design of attribute fusion is firstly the selection of the fusion structure. For the target recognition system used in different environments, the choice of attribute structure must have the performance of optimizing detection and recognition for a given target, as well as the technical ability (software and hardware). The constraints are also related to the quality of the sensor and the bandwidth of the transmitted data. From the perspective of the battlefield environment, it is common to use multiple types of sensors on different platforms (that is, using heterogeneous sensor data), and communication bandwidth cannot be large due to environmental factors. Firstly, the use of data-level fusion is less feasible. Simply using feature-level fusion to achieve multi-sensor target recognition will result in higher-dimensional feature vectors, which increases the complexity of the recognition system. And several data sources have been disturbed and destroyed, and the flexibility of the identification system has been tested; the decision-level has high flexibility in information processing, relatively low communication bandwidth and computer resources, and has the ability to process asynchronous information. Parallel structure and decision-level fusion have certain advantages in the application of multi-sensor target recognition in complex interference environments. But for this fusion itself, the information that has been fused has been processed, and many of the original information of the source has been lost in the process. This kind of information, especially in a dynamic and ever-changing environment, has a negligible effect on the correct classification and recognition of the system. This is also the limitation of the decision-level fusion itself. In this case, in order to make full use of various information without causing huge data processing, the decision-level integration needs to be further improved.

From the perspective of existing decision fusion algorithms, fusion is often performed only on the basis of decision information, and most of them do not fully utilize the redundant information provided by multiple sensors. In the dynamic and variable complex interference environment, it is not enough to only fuse redundant information. In order to fuse the reliability of the result, it is necessary to use various information to verify, analyze, supplement, coordinate and infer the information. In fact, the fusion here emphasizes the integration of “all information”. Therefore, the algorithm and structure should be organically combined, so that the multi-sensor system can adopt an effective fusion strategy according to the actual situation to improve the adaptability and robustness of the system.

2.2 Establishment of A Complex Dynamic Environment Analysis Module

For a multi-sensor target recognition system, the sensor is like a human sensory organ. It is the receiving window of the external environment information and target information. The environmental changes and external disturbances and damages directly affect the sensor detection performance. Therefore, the parameter provided by the environmental analysis module to the system is the performance indication of the sensor, which is based on the reliability of the sensor.

The accuracy and credibility of the sensor are different under different environments and conditions, and its role in data fusion should also change. Therefore, in data fusion, it is necessary to assign different credibility weights to each information according to the different real-time status of each sensor to ensure that it is properly utilized. The influencing factors of sensor credibility are often random, and most of these factors cannot be accurately described by numerical values, and the degree of influence on sensors varies with the type of sensors. In fact, sensor credibility estimation is a process of uncertainty information reasoning. In addition to some input environmental information, corresponding empirical information is needed. Due to the dynamic nature of the environment, the estimation of sensor credibility should be adaptive, self-learning, reasoning, fast processing speed and easy to implement. In this paper, neural network and fuzzy inference are used to estimate the sensor credibility, namely environmental analysis.

(1) Neural network-fuzzy inference theory

Neural network (NN) and fuzzy inference technology F(R) itself are two important tools for intelligent information processing and control. In the application, neither the NN nor the FR system need to establish a mathematical model based on the dynamic characteristics of the system. What the former needs is a training sample, which adapts to changes in the external environment through its structural variability, and has the ability to acquire and learn knowledge; the latter requires expert knowledge, experience, or operational data describing the rules, through various factors. The fuzzy semantic rules of mutual relations realize reasoning. The NN-FR inference system enables the traditional fuzzy inference system to have the ability to learn and associate, and the neural network structure is more transparent and improve its reasoning ability. If the full information state space of the system information is divided into digital information and fuzzy language information, the NN-FR inference system satisfies the basic conditions for achieving optimal information processing in the full information state space. This kind of system guarantees the acquisition of all information from the external structure, and realizes the intelligent information processing of all information in the internal structure and algorithm. The basic block diagram of the system is shown in Figure 2. It can be seen that the essence of the neural network-fuzzy inference system is different from the traditional inference system. The basic purpose is to adapt to the inexactity that is prevalent in the real world. The basic guiding ideology is direct. Applying human thinking methods, giving full play to the advantages of neural network adaptive learning and the functions of knowledge reasoning and decision making in fuzzy reasoning can effectively solve the problem of processing uncertain information.

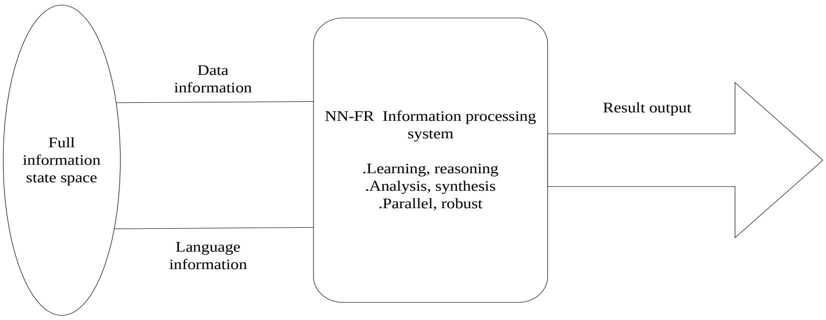

Figure 2: Full information state space information processing system

(2) ANFIS credibility discriminator structure

The credibility discriminator is implemented by a zero-order sugeno fuzzy adaptive neuro-fuzzy inference system (ANFSI). The structure of the system is shown in Figure 3.

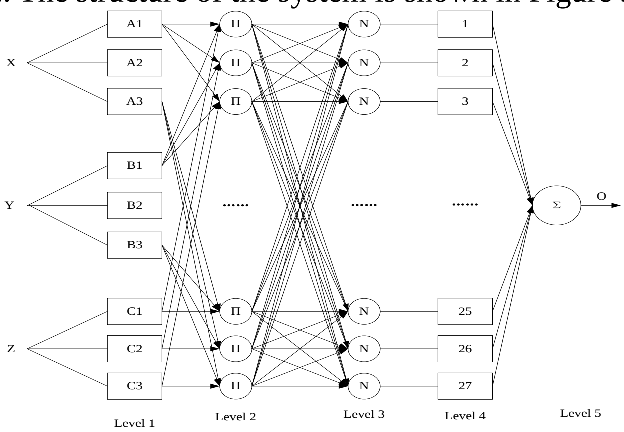

Figure 3: Structure of the ANFIS credibility discriminator

The characteristics of the structure: with fuzzy reasoning function; using neural network learning function, can adaptively adjust the parameters of the inference system, so that the learning samples can be used to correct the parameters of the fuzzy inference system; the hybrid learning method can realize the neural network training. The fast convergence of the system; the input and output of the system can be real values, and the fuzzy and defuzzification of the parameters are automatically completed by the system, so that the real data representing the properties and state of the sensor can be input into the system, so that the output is the real value representing the sensor reliability.

(3) Algorithm of ANFIS credibility discriminator

The nodes of the same layer in the network structure of ANFIS have the same type of functions, and the functions of the nodes of each layer will be discussed below. Here, the output of the j-th node of the *i*-th layer is denoted as O_{ij}.

Layer 1: This layer node is directly connected to the components of the input vector (X, Y, Z). Each node *i* has a node function, expressed as:

$$\begin{cases} O_{1,i} = \mu_{A_i}(X), i = 1,2,3 \\ O_{1,i} = \mu_{B_{i-3}}(Y), i = 4,5,6 \\ O_{1,i} = \mu_{C_{i-6}}(Z), i = 7,8,9 \end{cases} \tag{1}$$

Where X or Y or Z is the input of node *i*, and A_1, A_2, A_3 (equivalent to “normal”, “interference”, “destruction”) are fuzzy sets of nodes *i* (*i* = 1, 2, 3), B_1 , B_2, B_3 (equivalent to “high”, “medium”, “low”) are fuzzy sets of nodes *i* (*i* = 4, 5, 6), C_l, C_2, C_3 (equivalent to “good”, “better” , “Poor”) is a fuzzy set of nodes *i* (*i* = 7, 8, 9). However, O_1, *i* is the membership of an input belonging to the corresponding fuzzy set. μ_{A_i} (*i*=1,2,3), $\mu_{B_{i-3}}$ (*i*=4,5,6) and $\mu_{C_{i-6}}$ (*i*=7,8,9) are the membership functions of the corresponding nine fuzzy sets, which all adopt Gaussian functions, as shown below :

$$\mu_{A_i}(X) = \exp\left[-\left(\frac{X - c_i}{a_i}\right)^2\right] \qquad i=1, 2, 3 \tag{2}$$

Among them, $\{a_i, c_i\}$ is the premise parameter set. Changes in the values of these parameters cause the Gaussian function to change as well.

Layer 2: Each node of this layer is a fixed node labeled "n" whose input is the output of one of the three nodes of layer 1, and its output is the product of all input signals, for example:

$$O_{2,1} = \mu_{A_1} \cdot \mu_{B_1}(Y) \cdot \mu_{C_1}(Z) \tag{3}$$

The output O_2,*i* of the i-th node represents the activation strength of the i-th rule.

Layer 3: Each node in this layer is a fixed node labeled "N". The i-th node calculates the ratio of the activation intensity of the i-th rule from the previous layer to the sum of the activation intensities of all the rules, expressed as:

$$O_{3,i} = \frac{O_{2,i}}{\sum_{j=1}^{27} O_{2,j}}, i = 1,2,...,27 \tag{4}$$

The output of this layer node is called the normalized activation strength. If w_i is used to indicate the activation strength of the i-th rule, and $\overline{w_i}$ is used to represent the normalized activation strength of the i-th rule, the output of the layer node can be expressed as:

$$\overline{w_i} = O_{3,i} = \frac{O_{2,i}}{\sum_{j=1}^{27} O_{2,j}}, i = 1,2,...,27 \tag{5}$$

Layer 4: The output of each node *i* in this layer is

$$O_{4,i} = \overline{w_i} \cdot r_i, i = 1,2,...,27 \tag{6}$$

Where $\{r_i\}$ is the conclusion parameter set.

Layer 5: This layer consists of only one node. This single node is a fixed node labeled "Σ", which is a summing node whose output (ie the total output of the network) is the sum of all input signals of the node. Expressed as:

$$O = O_{5,1} = \sum_{i=1}^{27} O_{4,j} = \sum_{i=1}^{27} \overline{w_i} \cdot r_i \tag{7}$$

The discriminator uses prior experience and environmental information to reasonably reason and realize the estimation of sensor credibility in complex environments. The introduction of the environmental analysis module makes the attribute fusion have environmental adaptability, and the target recognition system is more intelligent.

3. Experiments

3.1 Experimental Background

In order to effectively realize classification and recognition, it is necessary to transform the original data to obtain the feature that best reflects the essence of the classification. This is the process of feature extraction and selection. Generally, the space composed of the original data is called "measurement space", and the space on which the classification identification is performed is called "feature space". By transforming, the pattern represented in the measurement space with a higher dimensionality can be changed to the pattern represented in the feature space with a lower dimensionality. Commonly used features are statistical features, structural features, mathematical transformation features and logical features. Since the characteristics of market customer demand are difficult to measure with sensors, etc., we need to identify the enterprise target can only use other characteristic information to reflect the specific situation of the market customer demand, so as to get the accurate identification of the target. The identification of customer needs is mainly identified from three aspects of management, service and operation.

(1) The identification of management is to identify the bottom line of the customer's expectations to determine a stable and economic management system based on the customer's basic expectations.

(2) The identification of services is mainly the feeling of customers receiving services, that is, the degree of customer perception of services.

(3) Identification of the business, through the analysis of the customer's behavior, record the purchase behavior of the customer and potential customers, identify the cause of the customer's purchase interest, and the purchase mode within a period of time to determine the customer's demand orientation.

3.2 Experimental Feature Extraction Criteria

When performing feature extraction and transformation, it is necessary to follow certain criteria, which can be constructed using the category separability criteria. In general, the class separability criterion can reflect the distribution of various types in the feature space, and can describe the importance and contribution of each feature component in the classification and recognition. Here we construct a distance-based separability measure and use this as a standard to extract the parameters of the AR model. For multi-class sample classification problems, the selected transform mode should maximize the distance between the mean vectors of different class modes, and the mode variance sums belonging to the same class should be the smallest. From another point of view, that is, the distance between the types is large, and the distance between the samples in the class is small.

Based on the above principles, the construction distance separability measure is as follows:

$$J_{\eta k} = \frac{d_{\eta k}}{\sigma_{ik} + \sigma_{jk}} \tag{8}$$

among them

$$d_{\eta k}^2 = \left(m_{ik} - m_{jk}\right)^2 \tag{9}$$

For the inter-class feature distance, m_{ik} and m_{jk} are the k-th dimension components of the average vector of the two types of target sample sets, respectively, and k is the sample dimension.

$$\sigma_{ik}^2 = \frac{1}{t-1}\sum_{c=1}^{t_1}\left(A_{ck} - m_{ik}\right)^2 \tag{10}$$

Wherein, A_{ck} is the k-th component value of the c-th sample of the i-th target eigenvector, and σ_{ik} σ_{jk} is the standard deviation of the k-th component of the i-th target and the j-th target eigenvector, respectively.

This distance separability measure has obvious physical meaning. It reflects the distance between the two types of mode mean vectors and their respective standard deviations. Obviously, the larger J, the better the separability of the pattern.

3.3 Experimental Feature Data Extraction

Using the above formula, the paper calculates the 20-order AR model parameter eigenvector separability measure for each of the 80 types of target management, service and management objectives. The results are shown in Table 1, the subscript symbols in the table. h, t, and c represent management, service, and operation, respectively, and the parameter vector order is arranged in descending order.

Table 1: Divisibility measures between management, service, and operations

Component number	J_{ht}	J_{tc}	J_{hc}	Component number	J_{ht}	J_{tc}	J_{hc}
1	1.7508	1.3289	0.28221	11	0.39246	0.50165	0.0445
2	0.4025	0.20615	0.23153	12	0.23496	0.081825	0.1841
3	1.09456	0.62722	0.65061	13	0.30614	0.254354	0.15662
4	0.72062	0.18093	1.6117	14	0.022302	0.3649	0.30885
5	2.6878	0.64665	4.3017	15	0.078616	0.46676	0.43932
6	2.033	0.59886	2.105	16	0.23131	0.37954	0.065488
7	1.1034	0.84074	1.7995	17	0.10502	0.43743	0.1169
8	0.19205	1.0103	1.1053	18	0.060541	0.44885	0.48277
9	0.50466	0.61542	1.2812	19	0.17734	0.25427	0.42082
10	0.81416	0.044224	1.1098	20	0.23504	0.23562	0.50121

Finally, the divisibility measures are decrementally sorted, and the components of the feature vectors corresponding to the larger divisibility measure values are selected as the final feature of the target recognition.

4. Discussion

4.1 Fusion Model Simulation and Analysis

(1) Simulation experiment setting

Suppose there are 3 sensors in the system and the target category is 3. Through the computer simulation, the target feature vector extracted by each sensor detection data is generated. Considering the representativeness and universality of the experimental results, the target feature vector of each sensor obeys the two-dimensional Gaussian distribution, and its distribution parameters are shown in Table 2. Based on these statistical distributions, the simulation generates a certain number of target feature samples. When a sample is given, the local identification information obtained by the neural network classification of the target features of each sensor is a three-dimensional vector, indicating that the feature samples of the target detected by the sensor belong to the posterior probability estimation of each category.

Table 2: Sensors provide distribution parameters for target features

Target category	m_x	m_y	σ_x	σ_y
1	0.8	1.3	0.4	0.5
2	0.3	1.0	0.4	0.5
3	1.1	0.7	0.4	0.5

The distribution parameter map of the sensor providing the target feature is shown in Figure 4.

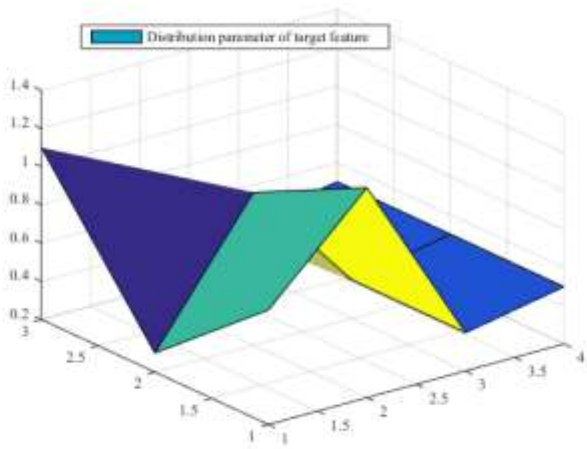

Figure 4: Sensor provides a distribution parameter map of the target feature

In the experiment, according to the feature vector distribution parameters, the sensor data of each sensor is simulated, and a different number of training sample groups are generated, which are 600 training samples, 200 in each class; 900 training samples, 300 in each class; training samples 1200, 400 in each category; 1,500 training samples, 500 in each category. A total of 1200 test samples were produced, each with 400. Then, using the generated training samples to train the BP neural network for local identification of each sensor, the outputs of these neural networks are directly or logarithmically combined and combined into vectors, and using these local recognition vectors to estimate the weights a_{stat} of statistical credibility in various fusion methods. In the least squares estimation, a_{stat} appears as a weight matrix; in neural network estimation, a_{stat} is reflected in the connection weight of neurons.

(2) Analysis of simulation results

In order to compare the sensor local classification identification result and the attribute fusion classification result. In Experiment 1, the number of training samples and test samples produced was 1,200, 400 in each class.

It is assumed that there is no external interference at this time, so the sensors are working normally, and the environmental reliability of each sensor is a_{dcd} value of 1.0. The recognition results of the obtained sensor and each attribute fusion algorithm are shown in Table 3.

Table 3: Identification results when the sensor is working normally

Classification identification	Goal 1	Goal 2	Goal 3	Average
	Recognition rate(%)			
Sensor 1	52.40	72.00	72.25	66.00
Sensor 2	74.00	63.50	47.50	62.50
Sensor 3	62.65	69.00	65.25	65.50
Equal weight	80.15	87.25	86.25	84.58
Least squares optimization	79.15	88.50	88.00	85.08
Single layer BP optimization	80.50	89.25	87.75	85.55
Three-layer BP optimization	79.00	88.50	86.75	85.00

The normal working recognition rate of the sensor is shown in Figure 5.

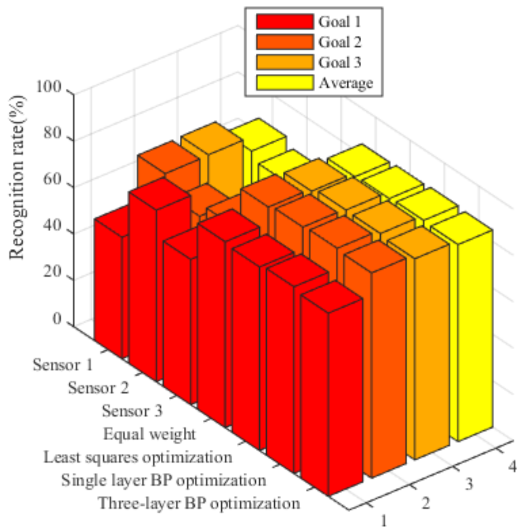

Figure 5: Sensor work identification diagram

It can be seen from Table 3 and Figure 5 that the consistent theory introduces the attribute fusion of multi-sensor target recognition, so that the recognition rate is greatly improved; the consistent rules used are different, and the degree of improvement of classification and recognition rate is also different. Under the same optimization mode, the recognition rate of LOGP is higher than LOP.

4.2 Simulation Experiment 2

In order to compare the performance of several optimization attribute fusion algorithms used in the paper, the results of several fusion algorithms are compared under different training samples.

Assume that all sensors are working properly at this time, and the environmental confidence of each sensor is adcd value of 1.0. The statistical confidence weights acond in the various fusion modes are estimated by using four training sample groups, and then the test samples are used for testing. The average recognition rate obtained is shown in Table 4.

Table 4: Fusion recognition results of different training samples when the sensor is working normally

Number of training samples Classification	600	900	1200	1500
	Recognition rate(%)			
Sensor 1Local identification	65.33	66.14	66.00	65.64
Sensor 2Local identification	62.47	63.64	62.10	63.00
Sensor 3Local identification	66.64	66.14	65.45	66.65
Equal weight	85.07	84.47	84.47	84.65
Least squares optimization	85.06	85.00	84.07	85.56
Single layer BP optimization	84.47	85.25	85.47	86.06
Three-layer BP optimization	85.17	84.72	85.00	86.00

The fusion recognition result of different training samples when the sensor works normally is shown in Figure 6.

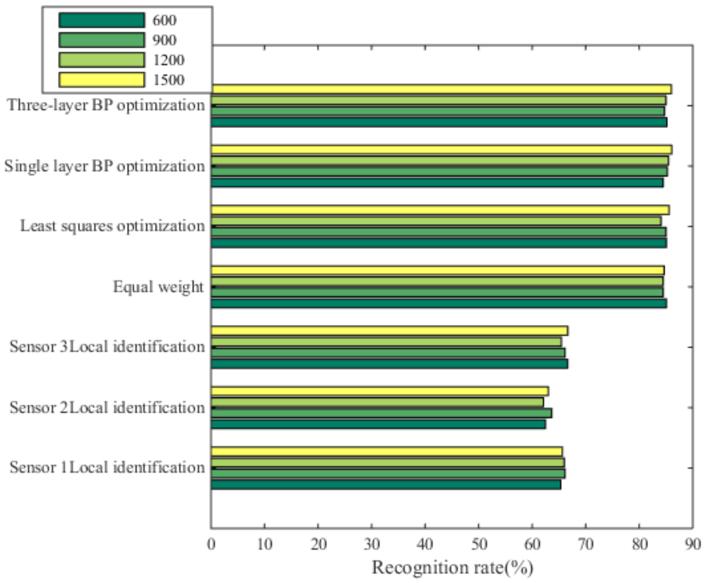

Figure 6: Fusion recognition results of different training samples when the sensor is working normally

It can be seen from the comparison of the results in Table 4 and Figure 6. With the increase of training samples, the fusion optimization of neural networks is more advantageous. This is because the nature of the neural network determines the more training samples, the more accurate the statistical rule mapping of the feature classification information; and the neural network approximates the aggregation function in the consensus theory in a nonlinear form, which is not a simple algebraic addition and subtraction relationship.

It is assumed that the sensor 1 is in an abnormal working state due to interference, and other sensors are working normally. Regardless of the environmental credibility, the average recognition results of the obtained sensor and each fusion algorithm are shown in Table 5.

Table 5: Fusion recognition results for different training samples when sensor 1 is disturbed

Number of training samples	600	900	1200	1500
Classification	Recognition rate(%)			
Sensor 1Local identification	45.75	46.25	47.42	47.72
Sensor 2Local identification	62.47	63.64	62.10	63.00
Sensor 3Local identification	66.64	66.14	65.45	66.65
Equal weight	72.00	71.50	73.30	72.06
Least squares optimization	73.80	70.42	72.57	73.05
Single layer BP optimization	74.72	72.07	74.15	73.55
Three-layer BP optimization	72.65	71.31	74.05	72.00

The fusion recognition result diagram under different training samples when the sensor 1 is interfered is shown in Figure 7.

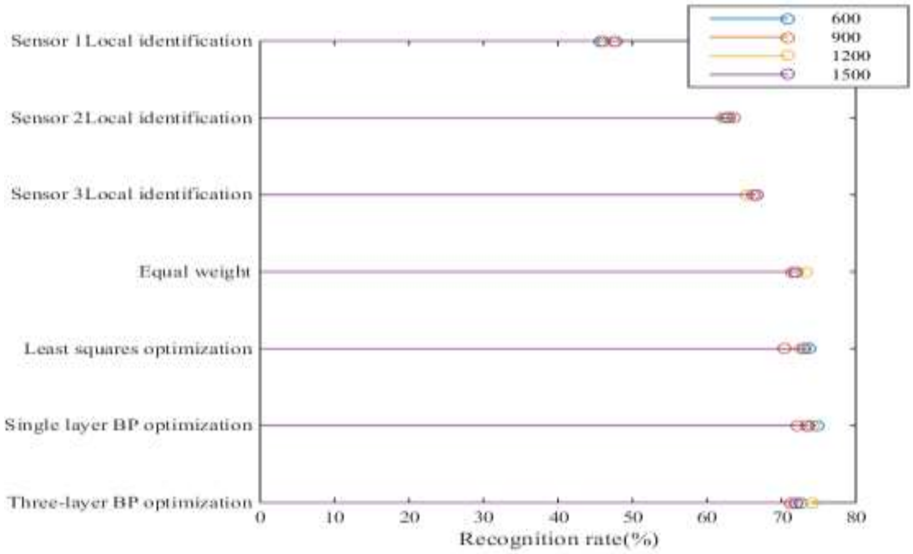

Figure 7: Fusion recognition results under different training samples when sensor 1 is disturbed

The neural network itself has a strong fault tolerance. When the sensor is disturbed, its optimal fusion still has a high recognition rate. Compared with single-layer BP neural network optimization, the anti-interference effect of three-layer BP neural network optimization fusion is better, because the three-layer neural network has stronger nonlinear mapping ability and better fault tolerance ability. Because the optimization fusion method based on logP is more sensitive to data changes, its robustness is worse than the optimization fusion of Lop.

This chapter mainly introduces the application of multi-sensor data fusion in enterprise identification. Firstly, the standard of customer requirement classification and the process of sensing node data collection are discussed. Then, on the basis of data preprocessing, we extract the customer demand features of each sensor and construct the multi feature market customer demand features through series fusion. Finally, through the experimental comparison and analysis, the BP neural network algorithm used in this paper achieves an accuracy of 92.73% in the enterprise identification market customer demand; then from the single sensor and multi-sensor aspects, it is proved that multi-sensor data fusion can effectively improve the accuracy of enterprise identification compared with single sensor.

5. Conclusions

The purpose of intelligent data fusion technology is to integrate the "full information" and realize the simulation of high-level human brain analysis and processing problems. How to use these diversified information to ensure the accuracy and robustness of the fusion system in the presence of uncertainty is the content of intelligent data fusion technology research. In this thesis, the multi-sensor target recognition in complex interference environment is taken as the application background, and the realization of intelligent attribute fusion is deeply studied. From the abstraction degree of information, the research of this paper belongs to the research of intelligent data fusion model and method. The algorithm and structure adopted can be applied to the high-level fusion processing of information in the fusion system. Therefore, the research content of this paper is in complex environment. The data fusion system has universal significance.

This paper proposes a model of intelligent attribute fusion for the problem of attribute fusion in the complex environment of enterprise identification market customer demand. Due to the complexity of the environment in the enterprise identification market, the sensor is affected by various factors, and the sensor information is uncertain, which makes the system robust and adaptive. Based on this analysis, this paper divides the intelligent attribute fusion into three modules: environmental analysis, uncertain information processing and classification and identification information fusion. The environmental analysis module directly affects the uncertain information processing module and the classification information fusion module. In this way, the structure of the fusion model can be arranged to solve the environment adaptability, robustness and flexibility required for data fusion in a dynamic and variable interference environment from different information levels and processing processes, and realize diversified information fusion. The fusion system is more intelligent.

The research results in this paper enrich and develop the data fusion theory system, which provides a new idea for the in-depth study of intelligent data fusion, and provides an effective algorithm for data fusion of multi-sensor target recognition in the complex environment of enterprise identification market customer demand. The application of technology to practical working systems is of great significance. Of course, data fusion is an interdisciplinary comprehensive theory and method. With the development of related fields, data fusion is also constantly changing and developing. There is still a lot of research work to be carried out.

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