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SENSITIVITY ANALYSIS OF HIERARCHICAL HYBRID FUZZY - NEURAL NETWORK

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Abstract- To identify the important attributes of complex system, which is high-dimensional and contain both discrete and continuous variables, this paper proposes a sensitivity analysis method of hierarchical hybrid fuzzy - neural network. We derive the sensitivity indexes of discrete and continuous variables through the differential method. To verify the effectiveness of our method, this study employed a man-made example and a remote sensing image classification example to test the performance of our method. The results show that our method can really identify the important variables of complex system and discover the relations between input and output variables; therefore, they can be applied to simplify the model and improve the classification accuracy of model.

Index terms: Hierarchical hybrid fuzzy - neural network, Sensitivity analysis, Differential method, Takagi-Sugeno model, Triangular membership function.

I. INTRODUCTION

A complex system usually involves high-dimension input variables both discrete and continuous. In the process of complex systems modeling, not all input variables are useful for the system output, and the number of high-dimensional will increase the system's complexity and instability. Therefore, selecting the important input variables to reduce the number of attributes and simplify model is necessary. In 2007, Wang D [1] proposed a novel hierarchical hybrid fuzzy neural network (HHFNN) to represent systems with mixed input variables. In 2009, Feng S [2] suggested a new training algorithm for HHFNN based on Gaussian membership function, which improved the accuracy of the model. In 2011, Yu XC [3] proposed a HHFNN algorithm based Lasso function for the interactive relationship between input variables, and got a better application in remote sensing image classification.

Sensitivity analysis is the study of how the uncertainty in the output of a mathematical model or system (numerical or otherwise) can be apportioned to different sources of uncertainty in its inputs [4]. The assumed model for the sensitivity analysis is expressed as $y = f(x_1, x_2, ..., x_n)$ (x_i is the *i*-th attribute value of the model). Each attribute is changed within the possible value range, so as to study and forecast the influence of the changes to these attributes on the output value of the model. We regard the influence degree as the sensitivity index of this attribute. The greater the sensitivity index, the more influence of this attribute is on the model output. The key purpose of the sensitivity analysis is to screen out the important attributes and simplify the model. With further study and development, the sensitivity analysis has been widely applied in many fields, such as in the ecological field, it is employed for the complicated ecosystem to screen out the attributes that play a leading role to the ecological model, and attention is attached in the ecological study and protection [5-9].

Classical sensitivity analysis algorithms are mainly three, respectively, based on mathematical statistics, neural networks and rough sets. The main sensitivity analysis methods based on the artificial neural network are: (i) the ‘Weights’ method is a computation using the connection weight, such as the Garson Algorithm [5] and Tchaban Method [6]; (ii) the ‘Partial Derivatives’ method consists in a calculation of the partial derivatives of the output according to the input variables, such as the Dimoponlos Method [7], Ruck Method [8] and Gevreya[10]; (iii) the

'Perturb' method corresponds to a perturbation of the input variables [11-12]; (iv) Sensitivity analysis method in combination with the statistical method [13-15]. Many datasets in actual applications often consist of high-dimension input variables with both discrete and continuous variables, and some discrete variables may play a crucial role in model. Classical sensitivity analysis method did not discriminate between discrete and continuous variables, or at the expense of loss information for continuous attributes discretization, resulting in inaccurate or erroneous analysis results.

In order to use sensitivity analysis methods extracting the important attributes of complex systems, and to achieve an accurate model of high-dimension input variables with both continuous variables and discrete variables, we proposes a sensitive analysis method of T-S hierarchical hybrid fuzzy - neural network (TS-HHFNN-SA) using the differential statistical method. The sensitivity indexes of discrete and continuous variables are calculated, and the input variables which are important to output of the system are obtained. To verify the effectiveness of our method, this study employed a man-made example and a remote sensing images classification example to test the performance of sensitivity index.

II. SENSITIVITY ANALYSIS OF HIERARCHICAL HYBRID FUZZY - NEURAL NETWORK

a. HIERARCHICAL HYBRID FUZZY - NEURAL NETWORK MODEL(HHFNN)

Hierarchical hybrid fuzzy-neural network[1] model consists of a fuzzy system and a neural network system, its topological structure is shown in Figure.1. In this model, fuzzy system is used to convert discrete variables to continuous variables; neural network system is used to deal with continuous variables and the intermediate output of the fuzzy system. In a word, this model is a good solution to the coexistence of discrete and continuous variables.

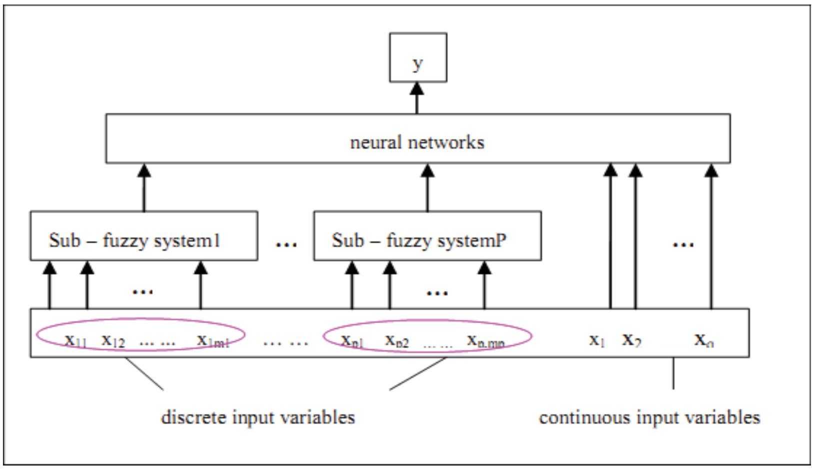

Figure 1: Structure of Hierarchical Hybrid Fuzzy-Neural Network

b. Sensitivity analysis of T-S HIERARCHICAL HYBRID FUZZY-NEURAL NETWORK (TS-HHFNN-SA)

With the training algorithm of HHFNN based on Lasso function proposed by Yu XC[3] in 2011, we propose a sensitivity analysis method of T-S hierarchical hybrid fuzzy - neural network in this study. Firstly, the sensitivity index of discrete variables in the fuzzy system is calculated. Secondly, the sensitivity index of the fuzzy system's output and the sensitivity index of the continuous variables in the neural network layer are calculated. Thus, the sensitivity index of the discrete variables and the continuous variables in HHFNN model can be obtained, and the important attributes can be determined according to their sensitivity index.

The inference rule in the paper [3] is expressed as follows:

If $x_{p,1}$ is $\mu_{p,1}^{j_1}$, and $x_{p,2}$ is $\mu_{p,2}^{j_2}$, ... , $x_{p,i}$ is $\mu_{p,i}^{j_i}$, ..., and x_{p,m_p} is $\mu_{p,m_p}^{j_{m_p}}$, then $y_p^{j_1 j_2 \cdots j_{m_p}} = f(X_p)$

where $x_{p,1}, x_{p,2}, ..., x_{p,m_p}$ are input variables , and m_p is the number of input variables, and $\mu_{p,i}^{j_i}$ is the membership of the input variable $x_{p,i}$ of the ***p***-th fuzzy system, $X_p = (x_{p,1}, x_{p,2}, ..., x_{p,m_p})$, $j_i \in \{0,1\}$, $i = 1, 2, ..., m_p$.

The output of the ***p***-th fuzzy system is calculated by the following formula:

$$\hat{y}_p(X_p) = \frac{\sum_{j_1 j_2 \cdots j_{m_p}} \left(\prod_{i=1}^{m_p} \mu_{p,i}^{j_i}(x_{p,i})\right) y_p^{j_1 j_2 \cdots j_{m_p}}}{\sum_{j_1 j_2 \cdots j_{m_p}} \left(\prod_{i=1}^{m_p} \mu_{p,i}^{j_i}(x_{p,i})\right)} \tag{1}$$

The neural network used in HHFNN model consisted of three layers: one input layer of $(P+Q)$ neurons (one for each input variable, where P is the number of the fuzzy systems, and Q is the number of the continuous variables.), one hidden layer of H neurons and one output layer of one neuron which is the output variable. $W_p = (w_{jp})_{H \times P}$ are the weights associated with the fuzzy system's output and the hidden layer neuron, and $W_Q = (w_{jq})_{HxQ}$ are the weights associated with the continuous inputs and the hidden layer neuron. $b = (b_j)_{1 \times H}$ are the biases of the neurons in hidden layer, and $g = (g_j)_{1 \times H}$ are the weights associated with the hidden layer and the output layer, and d is the bias of the neurons in output layer. The activation function of all neurons in the hidden layer represent as $f_1(x) = \frac{1}{1+e^{-x}}$, and the activation function of the output neuron is $f_2(x) = x$. The output of the HHFNN model is expressed as follows:

$$o = f(X) = f_2\left(\sum_{j=1}^{H} g_j h_j + d\right) = \sum_{j=1}^{H} g_j h_j + d \tag{2}$$

where $X = (X_1, X_2, ..., X_P, X_Q)$ are the inputs of the HHFNN model, and h_j is the output of the ***j***-th neuron in the hidden layer. h_j is calculated by the following formula:

$$\begin{aligned} h_j &= f_1\left(\sum_{p=1}^{P} w_{jp}\hat{y}_p + \sum_{q=1}^{Q} w_{jq}x_q + b_j\right) \\ &= 1/(1+e^{-(\sum_{p=1}^{P} w_{jp}\hat{y}_p + \sum_{q=1}^{Q} w_{jq}x_q + b_j)}) \end{aligned} \tag{3}$$

Then the output of the HHFNN model is expressed as follows:

$$o = \sum_{j=1}^{H} g_j / (1+e^{-(\sum_{p=1}^{P} w_{jp}\hat{y}_p + \sum_{q=1}^{Q} w_{jq}x_q + b_j)}) + d \tag{4}$$

Continuous variables are inputs of the neural network which is the upper layer in HHFNN model. The sensitivity index of continuous variables is calculated as:

$$s_q = \frac{\partial o}{\partial x_q} = \sum_{j=1}^{H} \frac{\partial o}{\partial h_j} \cdot \frac{\partial h_j}{\partial x_q} = \sum_{j=1}^{H} g_j h_j' w_{jq} \tag{5}$$

where $h_j' = h_j(1-h_j)$ represents the derivative of h_j.

Next, we give a detailed derivation of the sensitivity index of discrete variables in fuzzy subsystem and in HHFNN model. The sensitivity index of discrete variable $x_{p,i}$ which is the ***i***-th input of the ***p***-th fuzzy subsystem is caculated as follow:

$$s_{p,i} = \frac{\partial o}{\partial x_{p,i}} = \frac{\partial o}{\partial \hat{y}_p} \cdot \frac{\partial \hat{y}_p}{\partial x_{p,i}} \tag{6}$$

where $s_{p,i}$ is the sensitivity index of input $x_{p,i}$ in HHFNN model. $\frac{\partial o}{\partial \hat{y}_p}$ represents the sensitivity of the output in the ***p***-th fuzzy system, and written as $\hat{e}_p = \frac{\partial o}{\partial \hat{y}_p}$, and $\frac{\partial \hat{y}_p}{\partial x_{p,i}}$ represents the sensitivity of input variable $x_{p,i}$ in the fuzzy system, and written as $sf_{p,i} = \frac{\partial \hat{y}_p}{\partial x_{p,i}}$. Then

$$\hat{e}_p = \sum_{j=1}^{H} \frac{\partial o}{\partial h_j} \cdot \frac{\partial h_j}{\partial \hat{y}_p} = \sum_{j=1}^{H} g_j h_j (1-h_j) w_{jp} \tag{7}$$

The fuzzy system is T-S model, and $y_p^{j_1 j_2 \cdots j_{m_p}} = \sum_{i=1}^{m_p} a_{p,i}^{j_1 j_2 \cdots j_{m_p}} x_{p,i}$, $j_i = 0,1,2$. Then

$$sf_{p,i} = \frac{\sum_{j_1 j_2 \cdots j_{m_p}} \left(\prod_{k \neq i}^{m_p} \mu_{p,k}^{j_k}(x_{p,k}) \frac{\partial \mu_{p,i}^{j_i}}{\partial x_{p,i}} y_p^{j_1 j_2 \cdots j_{m_p}} + a_{p,i}^{j_1 j_2 \cdots j_{m_p}} \prod_{k=1}^{m_p} \mu_{p,k}^{j_k}(x_{p,k})\right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{m_p} \mu_{p,i}^{j_i}(x_{p,i})\right)} - \frac{\sum_{j_1 j_2 \cdots j_{m_p}} \left(\prod_{i=1}^{m_p} \mu_{p,i}^{j_i}(x_{p,i})\right) y_p^{j_1 j_2 \cdots j_{m_p}} \cdot \sum_{j_1 j_2 \cdots j_{m_p}} \left(\prod_{k \neq i}^{m_p} \mu_{p,k}^{j_k}(x_{p,k}) \frac{\partial \mu_{p,i}^{j_i}}{\partial x_{p,i}}\right)}{\left(\sum_{l=1}^{M} \left(\prod_{i=1}^{m_p} \mu_{p,i}^{j_i}(x_{p,i})\right)\right)^2} \tag{8}$$

where $\frac{\partial \mu_{p,i}^{j_i}}{\partial x_{p,i}}$ represents the partial derivatives of membership function of input variable $x_{p,i}$. The partial derivatives of input variable $x_{p,i}$ in triangle membership function is expressed as follow:

$$\frac{\partial \mu_{p,i}^{0}}{\partial x_{p,i}} = \begin{cases} \dfrac{-1}{c_{p,i} - \alpha_{p,i}}, & \alpha_{p,i} \le x_{p,i} \le c_{p,i} \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

$$\frac{\partial \mu_{p,i}^{1}}{\partial x_{p,i}} = \begin{cases} \dfrac{1}{c_{p,i} - \alpha_{p,i}}, & \alpha_{p,i} \le x_{p,i} \le c_{p,i} \\ \dfrac{-1}{\beta_{p,i} - c_{p,i}}, & c_{p,i} \le x_{p,i} \le \beta_{p,i} \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

$$\frac{\partial \mu_{p,i}^{2}}{\partial x_{p,i}} = \begin{cases} \dfrac{1}{\beta_{p,i} - c_{p,i}}, & c_{p,i} \le x_{p,i} \le \beta_{p,i} \\ 0, & \text{otherwise,} \end{cases} \tag{11}$$

where $\alpha_{p,i} < c_{p,i} < \beta_{p,i}$.

Thus, the sensitivity index of continuous and discrete variables in the HHFNN model can be calculated by the differential statistical method.

III. NUMERICAL EXAMPLE

In this study, we designed a function for class problem to test the performance of our method. In the function, there are ten input variables (x_1-x_{10}) and an output variable (Y). The relationship between the input and output variables are known in the function. The input variables of the function are in the range of 0–1, producing 800 training data and 200 testing data. The function will be used to verify whether the sensitivity indexes derived from our method can identify important variables and discover the relations between input and output variables. The function as follow:

$$\begin{aligned} Y &= a_1 x_1 + a_2(x_2 - 0.5) - a_3 x_3 + a_4 x_4 - a_5(x_5 - 0.5) \\ &- a_6 x_6 + a_7(x_7 - 0.5)^2 - a_8 x_8 x_{10} - a_9(x_9 - 0.5)^2 \end{aligned} \tag{12}$$

$$a_1 = 0; a_2 = 1; a_3 = 2; a_4 = 4; a_5 = 8;$$
$$a_6 = 0; a_7 = 1; a_8 = 2; a_9 = 4$$

When Y>0, the sample belongs to class 1; otherwise, class 2. In the Eq.(12), it is clear that the relationship between x_1-x_5 and the output variable is linear and increasing gradually, and that the relationship between x_7, x_9 and output variable is quadratic as well as increasing gradually, and that x_8 and x_{10} are interaction group. Assuming x_2, x_5, x_7 and x_9 are discrete variables producing randomly at the five value (0.2, 0.4, 0.6, 0.8, 1). In the experiment, two fuzzy subsystems are employed to process two groups of discrete variables which are randomly grouped (P=2). The optimal architecture (input-hidden-output) of neural network in HHFNN is 8-10-1. The sensitivity indexes of input variables(x_1-x_{10}) in BP neural network are shown in Figure.2. Using Eq.(5), the sensitivity indexes of continuous variables in HHFNN model are shown in Figure.3. Using Eq.(6)-(8), the sensitivity indexes of discrete variables in HHFNN model are shown in Figure4.

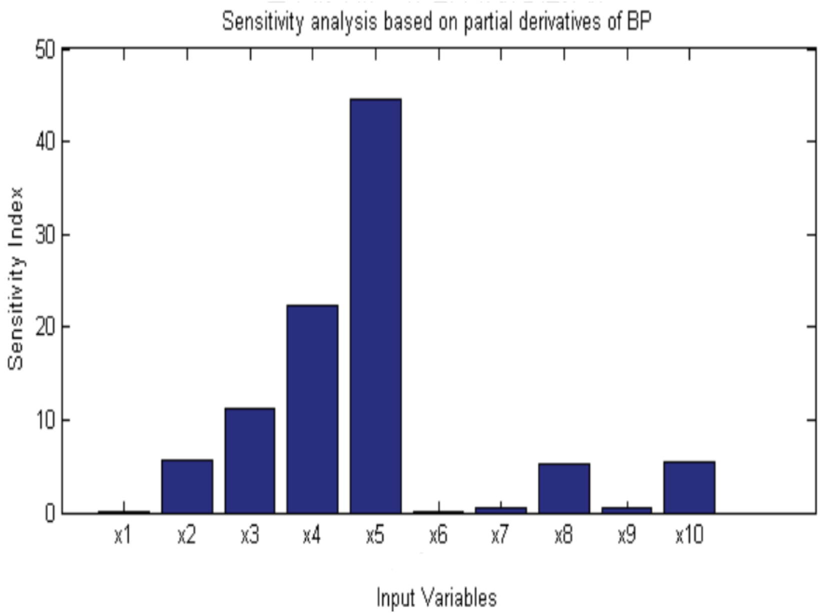

Figure 2: The sensitivity indexes of input variables in BP

Figure 2 illustrating the sensitivity index of input variables (x_1-x_{10}) in BP. As expected, the magnitudes of the indexes of x_1-x_5 increase gradually, and the index of x_5 is the most significant, and the indexes of x_1 and x_6 are very small and insignificant, and the indexes of the interaction variables (x_8 and x_{10}) are nearly equal. However, the sensitivity index missed to show the discrete variables x_7 and x_9 to be significant.

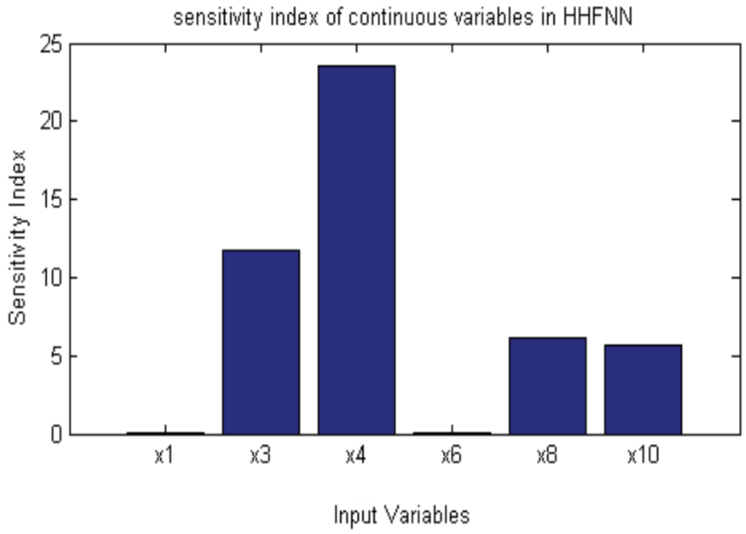

Figure 3: The sensitivity indexes of continuous variables in HHFNN

Using Eq.(5), the sensitivity index of continuous variables (x_1, x_3, x_4, x_6, x_8 and x_{10}) in HHFNN model is shown in Figure.3. The sensitivity indexes of continuous variables in HHFNN and in BP are nearly equal, because the continuous variables are the direct inputs to the BP neural network in HHFNN model, and they use the same calculation method.

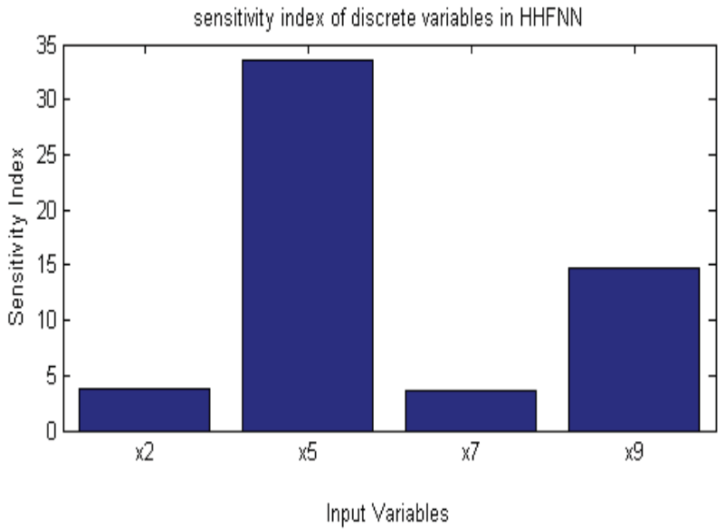

Figure 4: The sensitivity indexes of discrete variables in HHFNN

Figure.4 indicates the sensitivity indexes of discrete variables (x_2, x_5, x_7 and x_9) in HHFNN model. As expected, the index of discrete variable x_5 is the most significant, and x_9 is the second significant, and the discrete variables x_2 and x_7 have almost the same sensitivity indexes.

However, the sensitivity indexes of x_7 and x_9 are too small to show in Figure.2, and the sensitivity indexes of x_2 and x_7 have great difference. So we can see that our method can solve the problem for the quantitative evaluation of the mix inputs which contain both discrete and continuous variables, and can really identify the important variables of model. The sensitivity indexes of the mix inputs (discrete and continuous variables) in HHFNN model is shown in Figure 5.

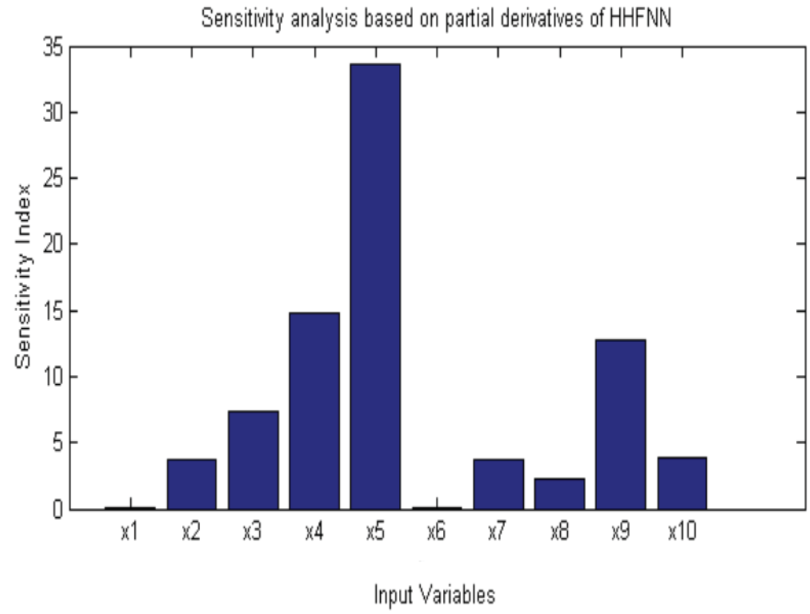

Figure 5: The sensitivity indexes of discrete and continuous variables in HHFNN

IV. EXPERIMENT AND ANALYSIS--REMOTE SENSING IMAGE CLASSIFICATION

a. Experimental Data

In this section, our method has been applied to the LANDSAT ETM+ remote sensing image of Zhangping and Anxi Pantian in Fujian Province of China acquired on May 11,2000(Fig.6). The purpose of the experiment is to test the accuracy of the sensitivity analysis method of extracting important variables and the effectiveness of the method applid to the remote sensing image classification.

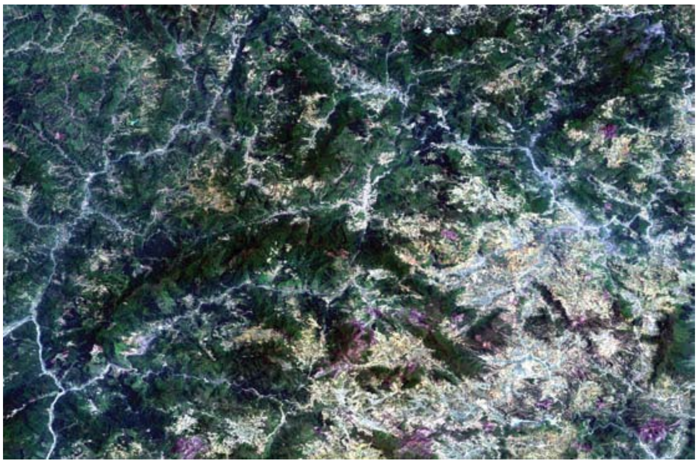

Figure 6: ETM+ 1-5, 7-band synthesized false color image of Zhangping and Anxi, Fujian Province

In the experiment, 6 bands (TM1, TM2, TM3, TM4, TM5 and TM7) are used with a spatial resolution of 30m. The image is of fine quality and clearly displays the situation of the land cover in Zhangping and Anxi in Fujian Province. By visual interpretation of the actual situation, surface features of the image are divided into such four categories as vegetation, rivers, exposed areas and shadows. In the experiment, a pixel is taken as one sample and ENVI4.6 employed to intercept sample data on the image. A total of 681 samples are obtained, of which 481 samples are planned for training and the other 200 samples are planned for testing to check the generalization ability of the network. Images of sample dataset with pixel values of the six bands of each sample are shown in Figure. 7.

Figure 7: Data of the training samples

b. Experimental Procedure

To provide sufficient image information during training, we increase two variables, Normalized Difference Vegetation Index (NDVI)[15]and Normalized Water Index (NDWI) [16]. They can be calculated as follow:

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \tag{12}$$

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{13}$$

On the above formula GREEN indicates the green band, and NIR the near infrared band, and RED the red band, which correspond respectively to 2, 4, and 3-band in the LANDSAT image. Calculation of NDWI can suppress the terrestrial vegetation information while highlight water information, the information can be effectively separated from the shadows. NDVI is sensitive to the changes in soil background. It eliminates the influence of topography and community structure, and weakens the interference of the atmosphere.

Pixel values of the 6 bands and the values of NDWI and NDVI are selected as 8 input variables of the HHFNN model. Since the attributes of remote sensing data are limited, 6 bands are randomly selected as discrete variables and the values of NDWI and NDVI as continuous variables (Q=2) in the experiment. Therefore, two fuzzy subsystems are employed to process two groups of discrete variables which are randomly grouped (P = 2).

Firstly, we employ HHFNN model in remote sensing image classification, then compare with the classification accuracy of BP. Secondly, we calculate the sensitivity indexes of the input variables in HHFNN and in BP, and the important inputs can be determined according to their sensitivity index (Tabel 1). Finally, we compare the classification accuracies of BP and of HHFNN using PD-BP-SA (Sensitivity analysis based on partial derivatives of BP) (Tabel 2), and compare the classification accuracies of BP and of HHFNN using our method (Tabel 3).

The flowchart of experiment is as follow:

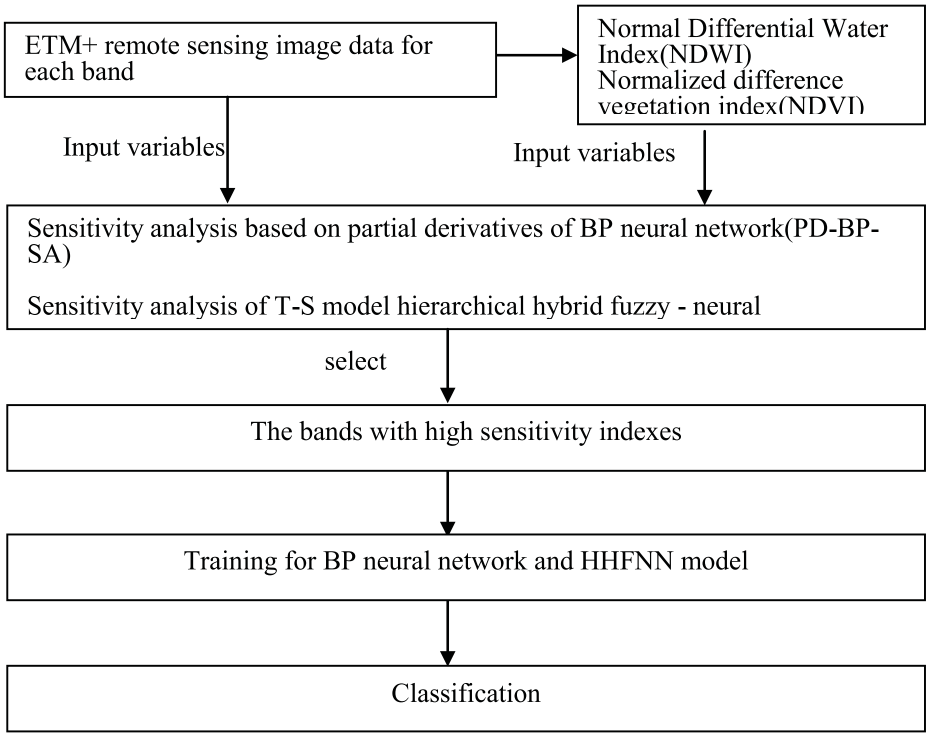

Figure.8 Experimental flowchart

c. Experimental Results and Analysis

By comparing the classification accuracy of HHFNN and BP with different hidden layer neurons, and learning rate, we found the classification accuracy of HHFNN are higher than the accuracy of BP (Figure 9), and the HHFNN is more effective than BP even in remote sensing image classification.

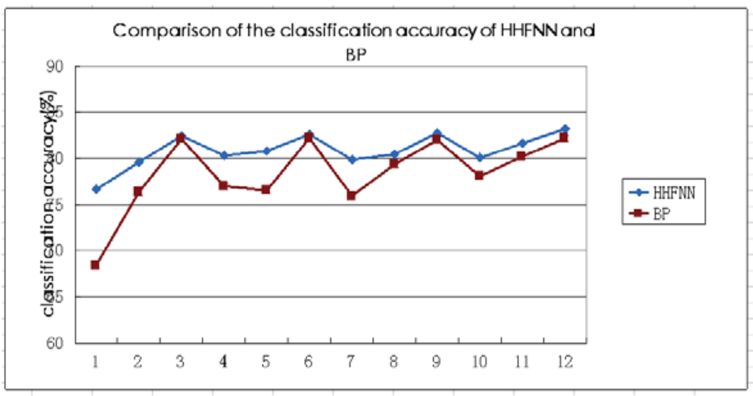

Figure 9: A comparison of the classification accuracies of HHFNN model with BP neural network

We calculated the sensitivity indexes of input variables and selected the important input variables to verify the validity of our method. Different sensitivity analysis methods of selecting input variables are shown in Table 1:

Table 1 The selected variables using sensitivity analysis

The sensitivity analysis	The selected variables
PD-BP-SA	TM1、TM2、TM3、TM4、TM5、TM7
Our method	TM1、TM2、TM3、TM4、NDVI

To get the best results, we established the optimal model with different network frameworks and learning parameters. The neurons of hidden layer are 5, and learning parameters is 0.05. The classification accuracies of BP and HHFNN model using sensitivity analysis as shown in Table 2 and Table 3, respectively.

Table 2 The classification accuracies of BP using sensitivity analysis

The sensitivity analysis methods		PD-BP-SA	Our method
classification accuracies	exposed areas	83.33%	83.33%
	vegetation	75%	85.41%
	rivers	61.43%	61.43%
	shadows	100%	100%
	Average accuracies	79.94%	82.54%

Table 3 The classification accuracies of HHFNN using sensitivity analysis

The sensitivity analysis methods		PD-BP-SA	Our method
classification accuracies	exposed areas	79.17%	85.42%
	vegetation	79.17%	100%
	rivers	71.43%	58.57%
	shadows	88.24%	88.24%
	Average accuracies	79.50%	83.06%

The results of both the sensitivity analysis methods of BP(PD-BP-SA) and our method are shown in Table 1. It can be seen that the input variables NDWI and NDVI were removed by using PD-BP-SA method, but NDVI is retained by using our method. Because the former method can not extract important input variables both discrete and continuous. The classification accuracies of BP and HHFNN with the input variables selected by PD-BP-SA and our method are shown in Table 2 and Table 3, respectively. It shows that the classification accuracies of our method of selecting important variables as input variables for HHFNN model is the highest. The results showed that our method can really identify the important variables which contain both discrete and continuous variables.

V. CONCLUSION

The hierarchical hybrid fuzzy neural network has been shown to be effective methods to solve problems with many mixed input variables, both continuous and discrete. Sensitivity analysis can help identify important input variables and discover the relations between input and output variables. Thus we proposed the sensitivity analysis method of HHFNN model, and we derived the sensitivity indexes of the mixed inputs both discrete variables and continuous variables in HHFNN model. A numberic example is employed to verify these sensitivity indexes of mixed inputs in this study. The results show our method could be use to solve the problem of the quantitative evaluation of the input variables which contain both discrete and continuous variables, and really identify the important variables. And with our method of remote sensing images classification we come to achieve good results.

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