

APPLICATION OF FUZZY REASONING TO ASSESSMENT OF CROP STRESS LEVEL BASED ON MODIS DATA: A FOCUS ON HEAVY METAL POLLUTION

Xiangnan Liu*, Nan Jiang, Xiaodong Wang, Chenxia Han

School of Information Engineering, China University of Geosciences, Beijing, China, 100083 - liuxncugb@163.com

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ABSTRACT:

This paper reviews the application of fuzzy theory and its combination with artificial neural-network technology for remote sensing information extraction. A dynamic fuzzy neural-network model is presented for crop heavy metal stress level assessment based on MODIS data. Hyperspectral vegetation indices, including NDVI, EVI and NDVIg, were used as input variables in this model for the purpose of enhancing and extracting weak information of crop heavy metal stress obtained from large-scaled farmland under complex circumstances. The output error and the root mean square error were considered as system performance evaluation factors. 250 samples, which contained values of hyperspectral vegetation indices and heavy metal stress levels, were prepared for the training process. And fuzzy reasoning rules were generated and evaluated based on their significance. At the end of the training process, this dynamic fuzzy neural-network model generated a total number of seven fuzzy rules. Another dataset, with 60 testing samples, was applied to evaluate the performance of this trained system. The result of this experiment indicated that this model was capable of extracting stress information with reasonable accuracy, which is over 95%, and thus it could be used as an effective tool in monitoring and managing agricultural environment.

1. INTRODUCTION

The estimation of crop heavy metal stress level in large scale farmland is essential for the management and protection of agricultural environment. Besides conventional methods, such as crop tissue analysis and soil sampling analysis, remote sensing technology has been applied to obtain more complete and accurate information. However, crop heavy metal stress is a kind of weak information without significant representation under complex circumstance. Therefore, it's difficult to classify crop stress level by traditional remote sensing information extraction methods. To solve this problem, fuzzy theory is applied in this study, and a dynamic fuzzy neural-network model is built and trained to classify crop heavy metal stress level.

Fuzzy neural-network (FNN) is defined as a combination of fuzzy theory and artificial neural-network technology, which is composed of fuzzy neurons, including fuzzy neurons describing "if-then" rules, fuzzy neurons with fuzzy output values and fuzzy neurons with fuzzy input values (Shao Dong et al., 1999). The greatest advantage of FNNs is their ability to model complex, non-linear process without having to assume the form of the relationship between input and output variables, that is to say, it's unnecessary to apply expert knowledge in these systems (Kwokwing Chau, 2006). Performance of a FNN system can be improved by means of modifying network architecture, such as "if-then" rules, membership functions and the significance of each rule. Considering that it is a useful technique for regression and classification problems, increasing attention has been paid in recent years to its application in remote sensing area. Researchers resorted to various network structures and learning algorithms to improve its efficiency and accuracy in extracting thematic information from remotely sensed data. And it has been found that FNNs have several advantages over traditional information extraction methods.

Firstly, they are non-linear models and thus have the capability to analyze complex data patterns. Secondly, they can process data at varied measurement scales such as continuous, ordinal and categorical data. So, they can describe and analyze fuzzy phenomena which are often encountered in practical applications (D.P. Kanungo et al., 2006). Thirdly, because of their ability to integrate non-spectral information into the networks in the form of additional input variables, they allow a better discrimination between vegetation spectral reflectance and plant stress level (Jesus Favela et al., 1998). By combining the power of ANNs for modelling complex phenomena, FNNs can provide better results than pure fuzzy logical approach. It is the particular intention of this study to remark upon the crop heavy metal stress detection and classification by means of fuzzy neural-network modeling based on hyperspectral remotely sensed data.

In this paper, a dynamic fuzzy neural-network (DFNN) model is presented to extract heavy metal contamination information in large scale areas under complex circumstance based on MODIS data. Values of hyperspectral vegetation indices, including NDVI, EVI and NDVIg, were used as input variables. Information to be represented by this network was fuzzy rules describing the relationship between input variables listed above and output crop heavy metal stress level. It was built and learnt from training data sets collected from typical heavy metal contaminated farmlands. According to experimental result, it was verified that this system was capable of extracting stress information from hyperspectral remote sensing data of large scale farmland with reasonable accuracy, and thus it could be used as an effective tool in monitoring and managing agricultural environment.

* Corresponding author.

2. FNN FOR REMOTE SENSING INFORMATION EXTRACTION

The FNN system should be trained in an iterative training process using the obtained training datasets. After updating this model for several times, the topological structure of this network and all the weighting indices describing the interconnection strengths between neighboring neurons are fixed. Then this model will be able to map input variables to an estimated output promptly and accurately.

Much of the previous FNN classification work in remote sensing has used multilayer feed-forward networks that are trained according to backpropagation algorithm (Martin Hellmann et al., 2002; Jiao Yunqing et al., 2007). But this training procedure is sensitive to the choice of initial network parameters. To overcome this problem, adaptive resonance theory is used to network development (Sucharita Gopal et al., 1999; Hasi Bagan et al., 2003). Another problem is that ancillary information applied in FNNs, which is useful to eliminate spectral ambiguities, may cause class proliferation, that is to say, too many clusters are created or many pixels are left unclassified. To address this problem, other methods, such as ID3 learning algorithm, are used to postprocess results obtained from fuzzy neural-networks (Jesus Favela et al., 1998).

Despite the recent progress, use of FNN technology in remotely sensed data processing is still in primary stage. The previous studies indicate that network learning algorithm, network topology structure, initialization of parameters and input signal presentations are important influencing factors to the performance of a FNN system (Wu Yifan, 2004; Zhang Qiang et al., 2006).

In the application of FNNs, training time and the accuracy of information extraction are important standards of system performance evaluation. The accuracy of network can be improved by increasing the number of nodes. But as the number of neurons increases, more time will be spent on network training and data processing. Therefore, the selection of appropriate network architecture and learning algorithm is of great importance. Besides, the output error of a FNN model is greatly depended on the completeness of the training datasets, which should cover all the possible cases that the system may be encountered (H. Noh et al., 2006). So, it's vital to prepare a typical field site for training data collection.

3. A DFNN MODEL FOR CROP HEAVY METAL STRESS ASSESSMENT

In this paper, a DFNN model is presented in order to extract crop heavy metal stress information from MODIS data. Quite unlike traditional FNNs, the architecture of this model is determined by training datasets instead of being predefined. As a result, it's unnecessary to apply expert knowledge in this model. Furthermore, all the fuzzy rules are generated or deleted according to the network performance and the significance of each rule during training procedure. So the amount of fuzzy rules generated by this model will not increase exponentially as the number of input variables increases.

It is remarked that this DFNN system is equivalent to a Takagi-Sugeno-Kang model (Min Han et al., 2008). And it can be described by the following formula:

$$f : \mathfrak{R}^r \rightarrow \mathfrak{R}^s :$$

$$y(x) = \omega_0 + \sum_{i=1}^u \omega_i R_i(\|X - C_i\|) \quad (1)$$

Where X ($X \in \mathfrak{R}^r$) = r-dimensional state vector with

$$X = [x_1, x_2, \dots, x_r]^T$$

x_i = the input variable of the DFNN system

r = the number of input variables

s = the number of output variables

u = the number of total fuzzy rules

ω_i = the significance of each rule

$R_i(\cdot)$ = activation function of the hidden units

$\| \cdot \|$ = the Euclidean norm

$C_i \in \mathfrak{R}^r$ = the centre of this system

ω_0 = the excursion value.

3.1 DFNN Structure Initialization

3.1.1 DFNN layers: This DFNN model includes one input layer, multiple hidden layers and one output layer. Hidden layers can be divided into fuzzifier and inference engine according to their functional aims. In fuzzifier layer, input values will be transformed into fuzzy values based on membership functions. Then, they will be analyzed by inference engine according to fuzzy reasoning rules obtained from training process. The output of hidden layers is crop heavy metal stress information described in the form of fuzzy values. Ultimately, in output layer, or defuzzifier layer, all these fuzzy output values will be transformed into certain values which represent the levels of crop stress induced by heavy metal contamination. Generally speaking, fuzzifier layer and inference engine layer compose the antecedent network which corresponds to the "IF" parts of rules. Consequent network consist of defuzzifier layer corresponding to the "THEN" parts of rules. The structure of this model is presented in Figure 1.

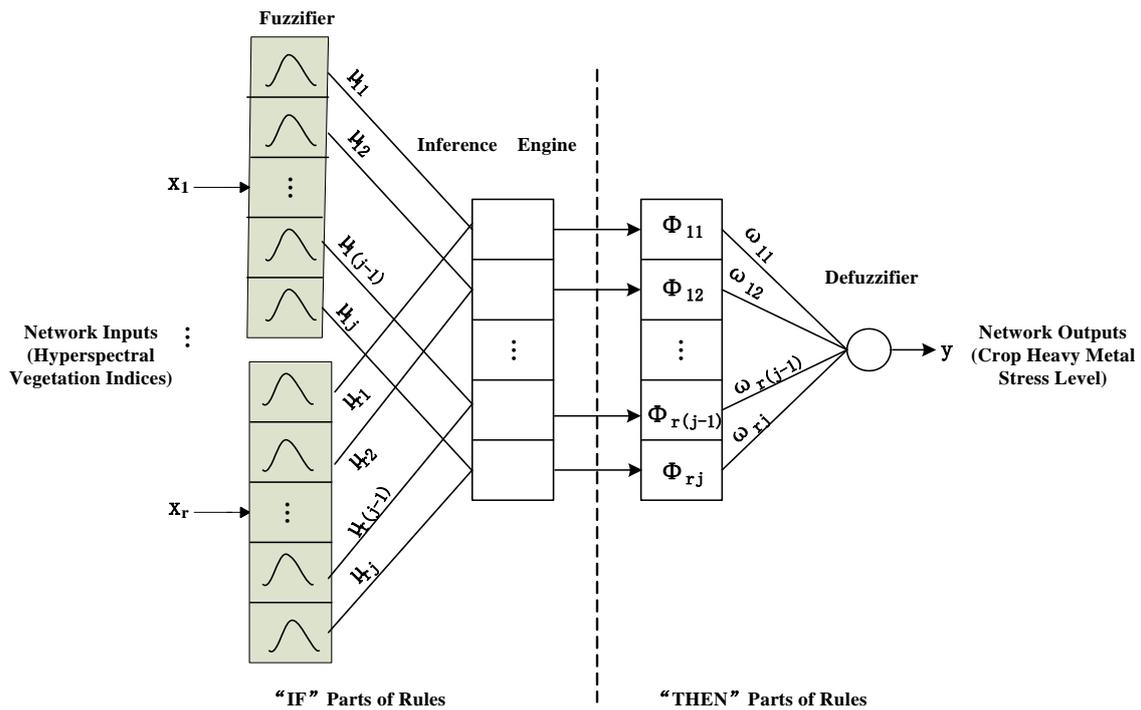


Figure 1. A schematic diagram of dynamic fuzzy neural-network model for crop stress level assessment

Each layer in a FNN model contains sufficient numbers of neurons which depend on the specific application. The neurons in a layer are connected to the neurons in the next successive layer and each connection carries a weight (Atkinson P.M. et al., 1997). In this model, the input layer receives the data from three hyperspectral vegetation indices. Hence, there are three neurons in this layer, corresponding to three influencing factors in crop stress level assessment. The hidden and output layers process the data actively. The number of hidden layers and their neurons are determined by trial and error (Gong, 1996). By varying the number of neurons in hidden layers, the neural

network is run for several times to identify the most appropriate neural network architecture based on training and testing accuracies. The number of neurons in output layers is determined in reference to the National Standard (GB15618-1995) and national food standards. Table 1 shows the soil heavy metal pollution classification standard. There are four values in output layer, corresponding to four levels of crop heavy metal stress, including pollution-free, light pollution stress, moderate pollution stress and severe pollution stress. They are presented by number 0, 1, 2 and 3.

Classification		As	Hg	Cd	Pb	Cr	Cu	Ni	Zn
		wl(mg.Kg ⁻¹)							
GB II	pH<6.5	40	0.3	0.3	250	150	50	40	200
	6.5<pH<7.5	30	0.5	0.3	300	200	100	50	250
	pH>7.5	25	1.0	0.6	350	250	100	60	300

Table 1. National Standard (GB15618-1995): Soil Heavy Metal Pollution Classification

3.1.2 DFNN input variables: Vegetation spectral reflectance is associated with the biochemical composition in leaves, such as structure of mesophyll cells, chlorophyll content and water content. In different wavelengths, vegetation spectrum reflectance curves show different patterns and characteristics (Yunzhao Wu et al., 2005). A number of studies have demonstrated that shifts in vegetation spectra due to heavy metal contamination occurred both the visible and the near-infrared part of the spectrum. These studies used spectral vegetation indices to investigate changes in plant stress, for they can combine two or more spectral bands to enhance the vegetative signal while minimizing background effects (Lehmann, F. et al., 1991; Sommer, S. et al., 1998; Mohammed et al., 2000; L. Kooistr et al., 2004). Heavy metal contamination will affect the status of plants, such as pigment contents, photosynthetic efficiency, nitrogen contents in canopy, and carbon contents of leaf. Values of NDVI, EVI and NDVIg can indicate the changes of these factors listed above. Therefore, they were chosen as the input variables in this model.

3.2 DFNN Training Algorithm

The aim of the training procedure is to minimize the error, i.e. the difference between the calculated output values and the target output values, and to generate fuzzy rules. The adaptation of the weights during the training process can lead to a so called over training problem. This means that the neural network can reproduce the training data quite well but has lost its ability to generalize. The phenomenon is especially severe when only a few training patterns are available.

Therefore, this model starts with a simple network structure which contains no fuzzy rules and goes over stepwise to more complicated structure. During training process, fuzzy rules will be generated according to the system performance. And in the meantime, insignificant rules will be deleted.

3.2.1 DFNN structure determination: In fuzzifier layer, input data are fuzzified and membership grades are calculated according to Gaussian membership function. The membership grade of each input value x_i ($i=1, 2...r$) is given by:

$$\mu_{ij}(x_i) = \exp\left[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \quad (i=1...r; j=1, 2... u) \quad (2)$$

Where μ_{ij} = the membership grade of x_i according to the j_{th} membership function

c_{ij} = the centre of the j_{th} membership function

σ_{ij} = the importance of the j_{th} membership function.

The output results obtained from this layer are then used as input values to the inference engine where T-norm product operator is applied to calculate the trigger weight of each rule. The output value of the j_{th} rule is computed according to the following function:

$$\phi_j(x_1, x_2, \dots, x_r) = \exp\left[-\sum_{i=1}^r \frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \quad (3)$$

The single node in defuzzifier layer is a fixed node labeled Σ , which computes the overall output as the summation of all incoming signals:

$$y(x_1, x_2, \dots, x_r) = \sum_{j=1}^u \omega_j \cdot \phi_j \quad (4)$$

Where y = the output results of this system

ω_j = the weight of the j_{th} rule

3.2.2 Rule extraction standards: Two standards, output error and the width of a Gaussian membership function, are introduced to determine whether a new rule should be added into current system.

To the i_{th} training data (X_i, t_i) , the output error can be computed as follows:

$$\|e_i\| = \|t_i - y_i\| \quad (5)$$

Where X_i = the input vector

t_i = the target output value

y_i = the calculated output value resulted from current system

In comparison with the predefined precision k_e , if

$$\|e_i\| > k_e \quad (6)$$

Then a new rule should be generated.

In this model, the input variables are classified into several fuzzy sets according to Gaussian membership function. The amount of overlap between data sets is controlled by the widths of Gaussian membership functions. An input training data can be present by a Gaussian membership function, if its membership grade is within the accommodation range.

To the i_{th} training data (X_i, t_i) , the distance between input value X_i and the center of Gaussian membership function can be computed as follows:

$$d_i(j) = \|x_i - c_j\| \quad (j=1, 2 \dots u) \quad (7)$$

Where u = the number of total fuzzy rules

c_j = the centre of Gaussian membership function.

In comparison with the accommodation criterion value k_d , if

$$\arg \min(d_i(j)) > k_d \quad (8)$$

Then a new rule should be generated.

3.3 Performance Evaluation

The performance of a FNN model should be evaluated based on following requirements (Ralf Wieland et al., 2008):

1. Accuracy: The error resulting between the calculated and target output values should be minimal;
2. Generalization: The model should reduce the complexity of the real world using an approximation of the data based on fundamental knowledge;
3. Portability: The model should be usable in different sites with slightly changed inputs compared to the training data.

Herein, the root mean square error (RMSE) and the output error were considered as statistical performance evaluation factors. To check the utility of this DFNN model, 250 samples containing hyperspectral vegetation indices values and heavy metal stress level information were applied to neural-network training process. And fuzzy rules were generated as is shown in Figure 2. During this process, a total number of eight fuzzy rules were generated. Considering the significance of each rule, one of them was deleted. At last, this training process generated seven fuzzy rules.

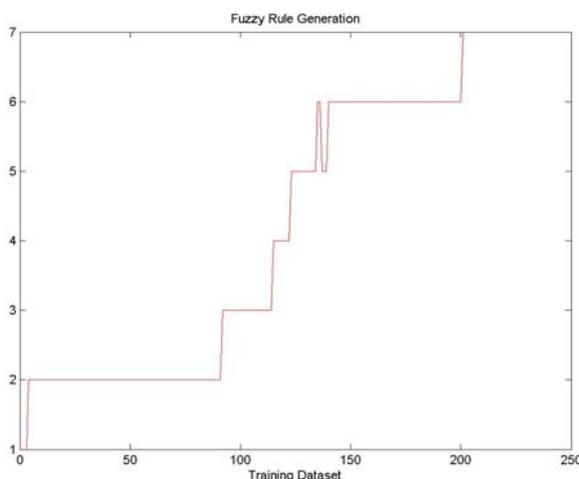


Figure 2. Generation of fuzzy rules based on 250 training samples obtained from MODIS data

Figure 3 presents the change of RMSE value during training procedure. The RMSE can be achieved less than 0.5 at the end

of this process. This result indicated that the best network architecture had been formed.

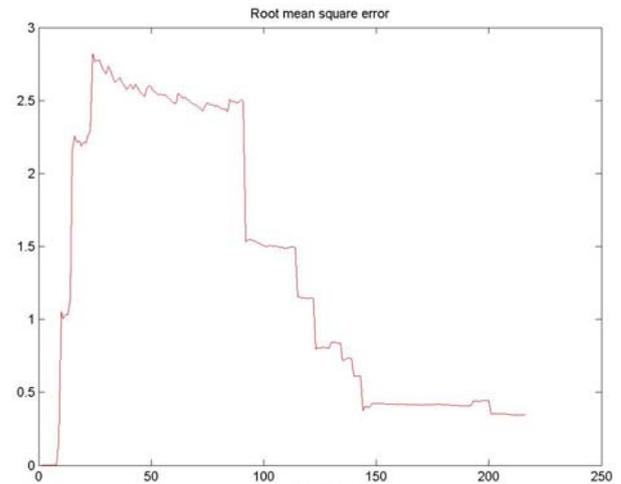


Figure 3. Root mean square error during training process based on 250 training samples obtained from MODIS data

Another dataset was prepared to evaluate the accuracy and generalization ability of this model. It was composed of 60 samples which were quite different from training data samples on crop heavy metal stress. The comparison of calculated and target outputs was shown in Figure 4. Three samples within these 60 testing samples were misclassified because their stress levels were distributed near the edge of two levels. According to the experimental result, this system achieve to an accuracy of 95% by a total number of seven fuzzy rules. It was confirmed that for crop heavy metal stress level assessment, this DFNN model can produce a satisfying recognition rates with minimal number of hidden neurons.

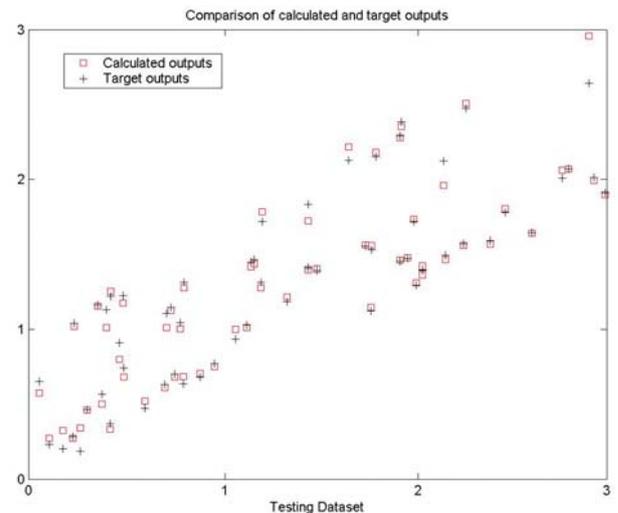


Figure 4. Comparison of calculated and target outputs based on 60 testing samples obtained from MODIS data

4. CONCLUSIONS

This paper presents a dynamic fuzzy neural-network (DFNN) model and its application to the assessment of crop heavy metal stress levels based on MODIS data. The proposed model uses hyperspectral vegetation indices as input variables in order to

enhance weak heavy metal stress information, and Gaussian membership function is adopted because of its non-constant differentiable character. Two standards, output error and the width of Gaussian membership function, are used to decide whether a new fuzzy rule should be added into this system. The significance of each rule is evaluated to decide whether a rule should be deleted. A training data set which is composed of 250 samples obtained from MODIS data is applied to adjust network structure and to generate fuzzy rules. On the basis of seven fuzzy reasoning rules, this system can achieve 95% accuracy. According to the result of experiment, the advantages of this DFNN model are summarized as follows:

1. It offers faster convergence and is less sensitive to both training and testing datasets;
2. It substantially decreases the number of hidden neurons which is crucial in the optimization of network structure, as fuzzy rules are generated or deleted according to the network performance and the significance of each rule;
3. It is capable of extracting crop heavy metal stress information with reasonable accuracy, and thus it could be used as an effective tool in monitoring and managing agricultural environment.

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