# A Weighted Fuzzy Min-Max Neural Network and Its Application to Feature Analysis*

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**Abstract.** In this paper, we present a modified fuzzy min-max neural network model and its application to feature analysis. In the model a hyperbox can be expanded without considering the hyperbox contraction process as well as the overlapping test. During the learning process, the feature distribution information is utilized to compensate the hyperbox distortion which may be caused by eliminating the overlapping area of hyperboxes in the contraction process. The weight updating scheme and the hyperbox expansion algorithm for the learning process are described. A feature analysis technique for pattern classification using the model is also presented. We define four kinds of relevance factors between features and pattern classes to analyze the saliency of the features in the learning data set.

## 1 Introduction

Many neuro-fuzzy methodologies for pattern classification and feature analysis have been proposed in the last decade[1-4]. Fuzzy Min-Max(FMM) neural network is a hyperbox-based pattern classification model[1-2]. In our previous work, a weighted fuzzy min-max(WFMM) neural network has been proposed[3]. The model employs a new activation function which has the weight value for each feature in a hyperbox. In this paper, we introduce an improved structure of the WFMM neural network and its application to feature analysis technique. We define four kinds of feature relevance measures to analyze the saliency of the features in the pattern classification problem. In the proposed model, the weight concept is added to reflect frequency factor of feature values. Since the weight factor effectively reflects the relationship between feature range and its distribution, the system can prevent undesirable performance degradation which may be caused by noisy patterns. Therefore the model can be used for the applications in which more robust and efficient classification performance is needed. The proposed feature relevance measures also can be utilized to select an optimal feature set for training. Through the experimental results using Iris data and Cleveland medical data[5], the usefulness of the proposed method is discussed.

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## 2 A Weighted Fuzzy Min-Max Neural Network

As shown in Equation (1), the model employs a new activation function which has the weight value for each feature in a hyperbox

$$b_j(A_h) = \frac{1}{\sum_{i=1}^{n} w_{ji}} \bullet \sum_{i=1}^{n} w_{ji}[\max(0, 1-\max(0, \gamma_{jiv} \min(1, a_{hi} - v_{ji}))) + \max(0, 1-\max(0, \gamma_{jiu} \min(1, u_{ji} - a_{hi}))) - 1.0] \tag{1}$$

In the equation, the $w_{ji}$ is the connection weight between $i$-th feature and $j$-th hyperbox, $n$ means the number of features in the test pattern, $\gamma$ is the sensitivity parameter in the range [0, 1]. $a_{ih}$ is the value of $i$-th feature of $h$-th input pattern. $u_{ji}$ and $v_{ji}$ mean the minimum and maximum value of dimension $i$ of hyperbox $b_j$, respectively. The original FMM neural network classifier is built using hyperbox fuzzy sets. The learning process is performed by properly placing and adjusting hyperboxes and weights in the pattern space[2].

The learning algorithm consists of hyperbox creation, expansion and contraction processes. The weight value increases in proportion to the frequency factor for each feature in the expansion process. The contraction process is to eliminate overlaps between hyperboxes that represent different classes. However it is considered as an optional part of our model. We define a new contraction method including the weight updating scheme. To determine if the expansion created any overlap, a dimension by dimension comparison between hyperboxes is performed. We define new scheme of overlapping handling techniques for four cases of overlaps. The proposed model is capable of utilizing the feature distribution and the weight factor in the learning process as well as in the classification process. Consequently the proposed model can provide more robust performance of pattern classification when the training data set in a given problem include some noise patterns or unusual patterns.

## 3 Feature Analysis

One of the advantageous features of the proposed model is a feature analysis capability. We can analyze the relationships between the features and the given classes from the weight data. In this paper we define four kinds of relevance factors as follows:

- $RF1(x_i, B_j)$ : the relevance factor between a feature value $x_i$ and a hyperbox $B_j$
- $RF2(x_j, C_k)$ : the relevance factor between a feature value $x_j$ and class $C_k$
- $RF3(X_i, C_k)$ : the relevance factor between a feature type $X_i$ and class $C_k$
- $RF4(X_i)$ : the saliency measure of feature $X_i$ for the given problem

These four factors are defined as Equation (2), (3), (4) and (5), respectively. In the equations, constant $N_B$ and $N_k$ are the total number of hyperboxes and the number of hyperboxes that belong to class k, respectively.

$$RF1(x_i, B_j) = w_{ij} \tag{2}$$

$$RF2(x_i, C_k) = (\frac{1}{N_k} \sum_{B_j \in C_k} S(x_i, (u_{ji}, v_{ji})) \cdot w_{ij} - \frac{1}{(N_B - N_k)} \sum_{B_j \notin C_k} S(x_i, (u_{ji}, v_{ji})) \cdot w_{ij}) / \sum_{B_j \in C_k} w_{ij} \tag{3}$$

$$RF3(X_i, C_k) = \frac{1}{L_i} \sum_{x_l \in X_i} RF2(x_l, C_k) \tag{4}$$

$$RF4(X_i) = \frac{1}{M} \sum_{j=1}^{M} RF3(X_i, C_j) \tag{5}$$

In Equation (3), $S$ is a function which measures the similarity between two fuzzy intervals. In Equation (4), $L_i$ is the number of feature values which belong to *i*-th feature. If the *RF2* has a positive value, it means an excitatory relationship between the feature and the class. But a negative value of *RF2* means an inhibitory relationship between them. A list of relevant features for a given class can be extracted using the *RF2* for each feature. The *RF3* shown in Equation (4) represents the degree of importance of a feature for classifying a given class. Therefore it can be utilized for feature selection or knowledge extraction process for pattern classification problems. The fourth measure, *RF4*, also can be defined in terms of the *RF3* as shown in Equation (5). The *RF4* means the saliency measure of a feature type for the given problem. We can utilize this information for the feature selection in designing process of the pattern classifier.

## 4 Experimental Results

We have developed a face detection model using the weighted FMM neural network for a real time robot vision system. In order to evaluate the proposed model and the feature analysis method, we have conducted the experiments using the Fisher's Iris data and the Cleveland medical data[5]. The Iris data set consists of 150 pattern cases in three classes (50 for each class) in which each pattern consists of four features. The Cleveland medical data consist of 297 pattern cases in five classes in which each pattern case has thirteen features. We have developed a hybrid neural network model for face detection by combining the proposed model with a convolutional neural network[4] which provides invariant feature extraction capability for distorted image patterns. From the feature analysis results using the proposed model, 1848 features extracted form the raw data have been reduced into 260 features without any performance degradation. For the Iris data and Cleveland medical data classifications, we have analyzed the relevance factors. Four kinds of analysis results have been generated as illustrated in Table 1. The table shows the relevance factors(*RF2*) between feature values and target classes for the Iris patterns.

**Table 1.** Relevance factors(RF2) between feature values and target classes(Iris data)

| Feature value | Target Class | RF2 |
|---|---|---|
| F4 : (0.0, 0.13) | Setosa | 0.312 |
| F1: (0.03, 0.22) | Setosa | 0.190 |
| F3: (0.51, 0.65) | Versicolor | 0.443 |
| F2: (0.13, 0.54) | Versicolor | 0.158 |
| F3: (0.65, 0.78) | Virginica | 0.272 |
| F2: (0.21, 0.67) | Virginica | 0.133 |

## 5 Conclusion

The proposed relevance measure *RF1* makes it possible to eliminate the hyperbox contraction process since the measure represents different relevance values within overlapped hyperbox feature ranges. The other measures also can be utilized in designing an optimal structure of the classifier. For examples, *RF2* and *RF3* can be used for a knowledge extraction method, and the *RF4* can be useful to select more relevant feature set for a given problem. The weighted FMM neural network model presented in this paper is capable of utilizing the feature distribution and the weight factors in the learning process as well as the classification process. We have applied the proposed model to a real-time face detection system in which there may be many unusual patterns or noise in the learning data set.

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