An Improved General Fuzzy Min-Max Neural Network for Pattern Classification

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Abstract. In this paper, a simple, yet effective, modification of the activation characteristic and training method of the general fuzzy min-max neural network is presented. The suggested method supplements the hyperbox definition with a frequency factor of the input training patterns. With this factor, a gain value is calculated based on the conception of the relevance of pattern density with respect to the hyperbox range. Utilizing this value, we propose an alternative training method that is able to replace the hyperbox contraction process. Thus, the classification results are independent of the class order presented in the training set. The effect of the gain value is analyzed and the result indicates that the proposed model is also less sensitive to distorted information.

Keywords: Pattern classification, neural network, general fuzzy min-max model, hyperbox.

1 Introduction

For the past few decades, various pattern recognition techniques have been developed progressively in the inductive machine learning field, and currently its application is widely practiced [1-4]. Speech recognition and character recognition systems are already in commercial use, and the more complicated forms of patterns such as images are actively being researched for a variety of applications.

With a given pattern space, classifiers are to divide the feature space into decision space by learning from the given training data. Mainly, there are two kinds of training methods. One is pattern classification by supervised learning, and the other is clustering by unsupervised learning.

For the supervised learning, Simpson introduced a fuzzy min-max (FMM) neural network based on fuzzy hyperbox sets representing the data clusters [5]. As a sequel to this, another FMM model for unsupervised learning was proposed by redefining the membership function and the hyperbox creation criteria [6]. A few years later, by integrating the classification and clustering features of the original two FMM models and generalizing some features, Gabrys and Bargiela developed a general fuzzy min-max (GFMM) neural network [7].

However, the FMM model, the basis of the GFMM neural network, has shortcomings in that classification results can be significantly affected by both the order of training patterns and small amount of distorted information. Therefore, the
operation of the GFMM network also shows these traits. For this reason, in [8], the classification performance of the FMM model was improved on the account of the frequency of training patterns.

In this paper, we employ the frequency factor used in [8] and apply it to the GFMM neural network and propose a model that is more stable and reliable. By analyzing the training effect, considering the frequency of patterns, we show that the replacement of the hyperbox contraction process is possible. For experimental evaluation, the Iris data and its attributes were selectively chosen and tested on the proposed algorithm.

The remainder of this paper is organized as follows. Section 2 provides a brief review on the original GFMM model. Section 3 describes how hyperbox contraction can affect the classification results. In section 4, the improvement of the hyperbox membership function and the training method is introduced. Section 5 analyzes the effectiveness of the suggested training method. Experimental evaluation is shown in section 6, and in the last section a conclusion is given on our research.

2 The Original GFMM Model

The modified features of the FMM model in the GFMM neural network can be described by four main points. First, the input can be fuzzy hyperbox sets as well as crisp-point patterns. Second, the membership function is modified to a form that uses fuzzy set operation, and the hyperbox expansion constraint has been changed. Third, the network is capable of being trained by both labeled data and unlabeled data and can perform classification and clustering separately or in combination. Lastly, the maximum hyperbox constraint can adaptively be changed.

The hyperbox defined by Simpson is defined in the GFMM model as the ordered set

\[ B_j = \{X_h, U_j, V_j, b_j(X_h, U_j, V_j)\} \]  \hspace{1cm} (1)

In this definition, the \( h \)th input pattern set \( X_h = [X_h^l, X_h^u] \), where \( X_h^l \) and \( X_h^u \) are vectors of the min point and max point of the input hyperbox, respectively. For hyperbox \( B_j \) in a \( n \)-dimensional space, \( U_j = (u_{j1}, u_{j2}, \ldots, u_{jn}) \) is the min point vector and \( V_j = (v_{j1}, v_{j2}, \ldots, v_{jn}) \) is the max point vector. The characteristic function \( b_j \) determines the membership value as follows:

\[ b_j(X_h) = \min_{i=1 \cdots n}(\min(1 - f(x_{hi}^u - v_{ji}, \gamma'), 1 - f(u_{ji} - x_{hi}^l, \gamma'))), \]  \hspace{1cm} (2)

where

\[ f(r, \gamma) = \begin{cases} 1 & \text{if } r\gamma > 1 \\ r\gamma & \text{if } 0 \leq r\gamma \leq 1 \\ 0 & \text{if } r\gamma < 0. \end{cases} \]  \hspace{1cm} (3)