

Role of Different Fuzzy Min- Max Neural Network for Pattern Classification

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Abstract: Different neural networks related to Fuzzy min-max (FMM) has been studied and amongst all, Enhanced Fuzzy min-max (EFMM) neural network is most recent. For classification of patterns a new Enhanced Fuzzy Min-Max (EFMM) algorithm has been studied. The aim of EFMM is to improve the performance and minimize the restrictions that are possessed by original fuzzy min-max (FMM) network. Three heuristic rules are used to improve the learning algorithm of FMM. First, to eliminate the problem of overlapping during hyperbox expansion, new overlapping rules has been suggested. Second, to discover other overlapping cases the hyperbox test rule has been extended. Third, to resolve the hyperbox overlapping cases, hyperbox contraction rule is provided.

Keywords: Fuzzy min-max (FMM) model, hyperbox structure, neural network learning, online learning, pattern, classification

1. Introduction

Artificial neural network (ANN) is a computational model that consists of an interconnected group of artificial neurons that replicates the biological neural system in our brain [1]. Nowadays, ANNs are used in different fields, e.g., power systems, healthcare and fault detection. Pattern classification is one of the active ANN application domains. For example, ANN models have been successfully applied to classification tasks in business and science and industrial fault detection and diagnosis [2].

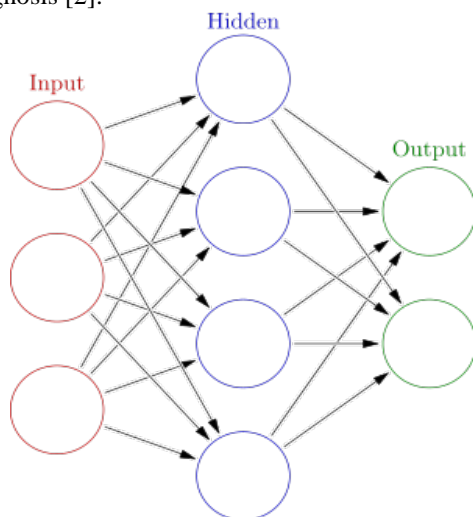


Figure 1: Showing the Layers in ANN

There are several salient learning properties associated with FMM.

- 1) Online learning: without losing old information, new information is learnt. This property is important to solve the stability plasticity dilemma.
- 2) Nonlinear separability: the ability to build a nonlinear decision boundary to separate distinct classes.
- 3) Overlapping classes: the ability of the nonlinear decision boundary to reduce misclassification by removing the overlapping regions of different classes.
- 4) Training time: the ability to learn and revise the nonlinear decision boundary with one-pass learning through the training data within a small training time.

2. Motivation

Artificial neural network (ANN) is a computational model that consists of an interconnected group of artificial neurons that replicates the biological neural system in our brain. Nowadays, ANNs are used in different fields, e.g., power systems, healthcare and fault detection. Pattern classification is one of the active ANN application domains [3]. For example, ANN models have been successfully applied to classification tasks in business and science [3] and industrial fault detection and diagnosis. To overcome a number of limitations of the original fuzzy min-max (FMM) network and improve its classification performance is the main motivation of EMFF. One of the main problems related to batch learning, such as in standard Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) in ANN, is catastrophic forgetting. Catastrophic forgetting is related to the inability of a learning system to remember what it has previously learned when new information is absorbed [4]. The back propagation ANN was found to form a new solution based on the most recent information only, when it was given two or more parts of information to learn [4]. This is different from the functionality of our brain. The catastrophic forgetting problem is also addressed as the stability plasticity dilemma which causes many issues in learning systems, e.g., how a learning system can be plastic enough to learn new knowledge and, at the same time, be stable enough to retain previously learned knowledge from corruption [4]. When an ANN has to learn from data samples in one-pass using an online learning strategy it becomes necessary to solve the stability plasticity dilemma. Fuzzy min-max (FMM) networks are proposed to overcome the problem of stability plasticity dilemma. A supervised classification model [5] and an unsupervised clustering model [6] are two networks suggested to overcome this problem.

3. FMM Related Networks

- FMM (Classification): This network [5] is used to serve for supervised learning. For higher level of decision making a fuzzy set approach to pattern classification is used. In this [5] relationship between the fuzzy sets and pattern classification has been

described. It explains how the fuzzy min-max classifier neural network works using learning and recalling algorithm. A neural network classifier that uses min-max hyperboxes as fuzzy sets that are combined into fuzzy set classes is introduced. The operations in the fuzzy min-max classifier are primarily adds and compares that can be implemented using relatively low single precision arithmetic operations. This simple design provides excellent opportunities for quick execution in parallel hardware.

- FMM (Clustering):

This network [6] is used to serve for unsupervised learning. The fuzzy min-max clustering neural network is constructed using hyperbox fuzzy sets. A hyperbox defines a region of the n-dimensional pattern space, and all patterns contained within the hyperbox have full cluster membership. A hyperbox is completely defined by its min point and its max point. There were several faults in the original fuzzy ART that has been corrected in this paper.

- General Fuzzy Min-Max (GFMM):

General Fuzzy Min-Max algorithm [7] is the fusion of both classification and clustering. This algorithm can be used as pure classification, pure clustering or hybrid clustering classification. In this [7] the classification results can be crisp or fuzzy. Similarly to the original methods the GFMM utilizes min-max hyperboxes as fuzzy sets. In GFMM the training of data is very fast, and as long as no identical data belonging to different classes, the recognition rate is 100%.

- Granular reflex Fuzzy Min-Max neural network (GrFMN):

In this paper [8] a granular neural network named Granular reflex Fuzzy Min-Max neural network is given. Granular or point data is used to train the network online. To tackle the data of different granularity(size), the neuron activation functions have been designed. The reflex mechanism in GrFMN was found useful to handle overlaps in granular data. This can learn the data online in a single pass through data and can be operated in distinct categories.

- Stochastic FMM:

The fuzzy min-max neural network [5] can be increasingly trained by appropriately adjusting the number of hyperboxes and their corresponding values. In this [9] the idea of random hyperbox and stochastic fuzzy min-max neural network has been proposed. Each hyperboxes is associated with stochastic learning automaton.

- Adaptive resolution min-max:

The automation degree of the training procedure is also important with generalization capability and noise robustness. The generalization capability of the original min-max classifier depends mostly on position and size of the hyperboxes generated during training. In this [10] the classification system is automatic, since the training algorithms do not depend on presentation order of pattern and no critical parameter must be set in advance by the user.

- Inclusion/Exclusion fuzzy:

In this [11], one or more fuzzy hyperbox defined by their corresponding minimum- and maximum vertices and the hyperbox membership function is used to describe each class. Inclusion hyperbox and exclusion hyperbox are the two types of hyperboxes created. With these two types of hyperboxes each class fuzzy set is represented as a union of inclusion hyperboxes of the same class minus a union of exclusion hyperboxes. It is based on novel representation of class sets as a difference of two types of fuzzy sets (the union of hyperboxes belonging to the given class and the union of hyperboxes belonging to different classes).

- FMM with Compensatory Neuron (FCMN):

To represent the pattern classes, FCMN uses hyperbox fuzzy sets. The concept of compensatory neuron [12] comes from how human brain works at difficult conditions. The use of the contraction process is avoided by FCMN, reduces errors caused by it. Since the hyperboxes that are already created are not contracted, FCMN can retain the knowledge of the already learned patterns more efficiently than FMNN and GFMN. It is [12] based on the reflex mechanism of human brain, learns the data online in a single pass of data, and maintains simplicity.

- Data Core based FMM Neural Network (DCFMM):

For classifying the neurons of DCFMM a new membership function has been defined in which the data core, the noise and the geometric center of the hyperbox are considered. A new membership function [13] based on the data core is used instead of contraction process of the FMNN. To show the overlapping areas of hyperboxes of different classes, the membership function is added to neural network. Considering the effect of data core and the noise, still DCFMM has high accuracy and strong robustness. It is [13] used for pattern classification of pipeline system in laboratory.

- Modified FMM (MFMM):

In attempt to improve the classification performance of FMM when few numbers of large hyperboxes are formed in the network [14], some modifications are done. A new input pattern is given; Euclidean distance measure is used for predicting the target class associated with the new input and also the fuzzy membership function of the input pattern to the hyperboxes formed in FMM has to be measured. In this [14] a rule extraction algorithm is also enclosed. For each FMM hyperbox a confidence factor is calculated, and a user-defined threshold is used to prune the hyperboxes with low confidence factors.

- Modified FMM with Genetic Algorithm (MFMM-GA):

It is [15] a two stage classification of pattern and extraction of rule process. The first stage consists of Modified Fuzzy min-max (MFMM) classifier and the second stage is based on the genetic algorithm (GA) based classifier. To reduce the number of features in the extracted rules, a "don't care" approach is selected by the GA rule extractor and fuzzy if-then rules are extracted from the modified FMM classifier. The MFMMGA has number of new properties. First, a modified FMM has been proposed that uses a pruning procedure to eliminate

hyperboxes with low confidence factor. Second, the system uses GA rule extractor to select and produce compact rule set with more classification accuracy. Third, a rule extraction procedure to extract fuzzy if-then rules with “don’t care” antecedents has been presented.

• Offline and Online FMM-CART:

A new approach [16, 17] to classify and detect faults using a hybrid fuzzy min-max (FMM) neural network and classification and regression tree has been proposed. It [16] uses the concept of FMM for the purpose of classification and CART is used for rule extraction process. It also supports the offline and online learning properties for fault detection and diagnosis process.

4. Enhanced Fuzzy Min-Max Neural Network

Hyperbox Expansion Rule: The existing FMM expansion process can cause possible overlapping regions of hyperboxes from different classes in subsequent operations. To solve this problem, a new constraint is given, as follows:

$$Max_n(W_{ji}, a_{hi}) - Min_n(V_{ji}, a_{hi}) \leq \Theta$$

Based on the above equation each dimension of the jth hyperbox is inspected separately to determine whether it surpass the expansion coefficient (Θ). The expansion process is applied if and only if all hyperbox dimensions do not surpass Θ .

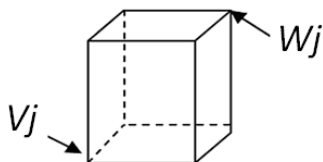


Figure 2.3: D Hyperbox

During the expansion process, FMM computes the sum of all dimensions and checks the resulting score with ($n\Theta$). This can strongly lead to some overlapping areas between hyperboxes from different classes. However, EFMM considers each dimension separately and compares the difference between the maximum and minimum points of each dimension against Θ individually.

Hyperbox Overlap Test Rule: Identifying all overlapping cases is insufficient during the hyperbox overlap test. Additional cases are used to tackle this problem, to detect other possible overlapping areas [4]. When one of the following nine cases is met then an overlapping area exists.

Case 1 :

$$V_{ki} < V_{ji} < W_{ji} < W_{ki}, \delta^{new} = \min(W_{ji} - V_{ki}, \delta^{old})$$

Case 2:

$$V_{ki} < V_{ji} < W_{ki} < W_{ji}, \delta^{new} = \min(W_{ki} - V_{ji}, \delta^{old})$$

Case 3:

$$V_{ji} = V_{ki} < W_{ji} < W_{ki} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 4:

$$V_{ji} < V_{ki} < W_{ji} = W_{ki} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 5:

$$V_{ki} = V_{ji} < W_{ki} < W_{ji} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 6:

$$V_{ki} < V_{ji} < W_{ki} = W_{ji} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 7:

$$V_{ji} < V_{ki} \leq W_{ki} < W_{ji} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 8:

$$V_{ki} < V_{ji} \leq W_{ji} < W_{ki} \\ \delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$$

Case 9:

$$V_{ki} = V_{ji} < W_{ki} = W_{ji}, \delta^{new} = \min(W_{ki} - V_{ji}, \delta^{old})$$

Assuming that $\delta^{old} = 1$ at beginning, by carrying out a dimension by dimension inspection, an overlapping area is found when $\delta^{old} - \delta^{new} < 1$. Then, by setting $\Delta = i$ and $\delta^{old} = \delta^{new}$, the overlap test checks the next dimension. The test stops when no more overlapping areas are detected. In this case, $\delta^{old} - \delta^{new} = 1$.

Hyperbox Contraction Rule: The contraction rule is created based on the cases of the hyperbox overlap test. Here, all cases are tested to find a proper adjustment. Note that case 1 and 2 are existing cases in FMM others cases are newly proposed cases of EFMM.

Case 1:

$$V_{j\Delta} < V_{k\Delta} < W_{j\Delta} < W_{k\Delta} \\ W_{j\Delta}^{new} = V_{k\Delta}^{new} = \frac{W_{j\Delta}^{old} + V_{k\Delta}^{old}}{2}$$

Case 2:

$$V_{k\Delta} < V_{j\Delta} < W_{k\Delta} < W_{j\Delta} \\ W_{k\Delta}^{new} = V_{j\Delta}^{new} = \frac{W_{k\Delta}^{old} + V_{j\Delta}^{old}}{2}$$

Case 3:

$$V_{j\Delta} = V_{k\Delta} < W_{j\Delta} < W_{k\Delta}, V_{k\Delta}^{new} = W_{j\Delta}^{old}$$

Case 4:

$$V_{j\Delta} < V_{k\Delta} < W_{j\Delta} = W_{k\Delta}, W_{j\Delta}^{new} = V_{k\Delta}^{old}$$

Case 5:

$$V_{k\Delta} = V_{j\Delta} < W_{k\Delta} < W_{j\Delta}, V_{j\Delta}^{new} = W_{k\Delta}^{old}$$

Case 6:

$$V_{k\Delta} < V_{j\Delta} < W_{k\Delta} = W_{j\Delta}, W_{k\Delta}^{new} = V_{j\Delta}^{old}$$

Case 7(a):

$$V_{j\Delta} < V_{k\Delta} \leq W_{k\Delta} < W_{j\Delta} \text{ and } (W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta}), V_{j\Delta}^{new} = W_{k\Delta}^{old}$$

Case 7(b):

$$V_{j\Delta} < V_{k\Delta} \leq W_{k\Delta} < W_{j\Delta} \text{ and } (W_{k\Delta} - V_{j\Delta}) > (W_{j\Delta} - V_{k\Delta}), W_{j\Delta}^{new} = V_{k\Delta}^{old}$$

Case 8(a):

$$V_{k\Delta} < V_{j\Delta} \leq W_{j\Delta} < W_{k\Delta} \text{ and } (W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta}), W_{k\Delta}^{new} = V_{j\Delta}^{old}$$

Case 8(b):

$$V_{k\Delta} < V_{j\Delta} \leq W_{j\Delta} < W_{k\Delta} \text{ and } (W_{k\Delta} - V_{j\Delta}) > (W_{j\Delta} - V_{k\Delta}), V_{k\Delta}^{new} = W_{j\Delta}^{old}$$

Case 9(a):

$$V_{j\Delta} = V_{k\Delta} < W_{j\Delta} = W_{k\Delta} \\ W_{j\Delta}^{new} = V_{k\Delta}^{new} = \frac{W_{j\Delta}^{old} + V_{k\Delta}^{old}}{2}$$

Case 9(b):

$$V_{k\Delta} = V_{j\Delta} < W_{k\Delta} = W_{j\Delta}$$

$$W_{k\Delta}^{new} = V_{j\Delta}^{new} = \frac{W_{k\Delta}^{old} + V_{j\Delta}^{old}}{2}$$

When the maximum point (W_j) of one or more dimension that belongs to a hyperbox (i.e., H_j) is enlarged and becomes totally overlapped with another hyperbox, (i.e., H_k), EFMM uses case 9(a) to perform contraction. Likewise, case 9(b) is applied when the minimum point (V_j) of one or more dimension that belongs to H_j is enlarged and becomes totally overlapped with H_k . [4]

5. Conclusion

In this paper, different Fuzzy Min-Max related neural networks have been studied. FMM is a useful online learning model that is able to overcome the stability-plasticity dilemma. Amongst all, Enhanced Fuzzy min-max (EFMM) neural network is most recent. There are three heuristic rules in EFMM to enhance its learning algorithm. First, a new hyperbox expansion rule is given to reduce the FMM classification errors by reducing the overlapping areas of hyperboxes that belong to distinct classes during the expansion process. Second, the existing hyperbox overlap test is expanded so that all overlapping areas from hyperboxes that belong to distinct classes can be identified. Third, a new hyperbox contraction rule to solve different overlapping cases that are not covered by the existing hyperbox contraction process is derived.

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