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An Enhanced Fuzzy Min-Max Neural Network Based on Pruning Algorithm for Pattern Classification

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Abstract: Various neural networks has been studied based on Fuzzy Min-Max (FMM) for classification of patterns. An Enhanced Fuzzy Min-Max (EFMM) neural network is recent one. The contribution of EFMM is ability to overcome a number of limitations of the original FMM network and increases the performance. The key contributions are three heuristic rules to enhance the learning algorithm of FMM. First, a new rule of hyperbox expansion is introduced to eliminate the overlapping problem which occur while process of hyperbox expansion. Second, other possible overlapping cases are discovered by using newly introduced hyperbox overlap rule. Third, a new hyperbox contraction rule to resolve possible overlapping cases is provided. Due to these rules, EFMM is more complex than FMM. Hence a concept of pruning is introduced in this paper. Confidence factor is used for pruning the hyperboxes and confidence factor is baes of frequency of use and its accuracy of recognition. Pruning of hyperboxes is done to minimize the hyperboxes and improve the network complexity of EFMM, but the recognition rate decreases slightly.

Keywords: Artificial Neural Network, Fuzzy Min-Max Neural Network, Enhanced Fuzzy Min-Max Neural Network, Pruning

I. INTRODUCTION

Artificial Neural Network (ANN) is a computational model that consists of an interconnected group of artificial neurons. ANNs are used in many fields, e.g., medical field, control systems field and also in fault detection. Pattern classification is one of the active ANN application domains. As an example, ANN are useful for classification tasks in various fields such as fault detection in science, industry and business and its diagnosis [1].
There are several salient learning properties associated with FMM.

1) Online learning: it is ability to learn new information without losing old information. This is important to solve the problem called stability plasticity dilemma.
2) Nonlinear separability: to separate distinct classes a nonlinear boundary is made.
3) Overlapping classes: it is a process of removing the overlapping regions of different classes to reduce misclassification.

In training process of ANN, the key problems related to batch learning is catastrophic forgetting. Catastrophic forgetting is lack of ability of a learning system to remember the previously learned while learning of new information is in process. The backpropagation ANN was found helpful to create a solution based on recent information only, when two or more pieces of information is provided to network. This is obviously different from the functionality of our brain. The problem of catastrophic forgetting problem is also termed as the stability plasticity dilemma. The dilemma reports several important issues in learning systems, e.g., how a learning system can be elastic enough to learn new knowledge and, at the same time, be stable enough to retain previously learned knowledge from corruption. Solving the stability plasticity dilemma is crucial especially when an ANN has to learn from data samples in one-pass using an online learning strategy. To overcome the stability-plasticity dilemma, a number of ANN models have been proposed, which include the adaptive resonance theory (ART) networks [2] and FMM networks [3].

II. LITERATURE SURVEY

Simpson [3] suggested the fuzzy Min-Max network. This network is used to assist for supervised learning. This describes the relationship between the patterns and fuzzy sets. 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 addition and compares that can be implemented using relatively low single precision arithmetic operations. This simple design offers excellent chances for fast execution in parallel hardware.

A general fuzzy Min-Max (GFMM) neural network developed by B. Gabrys and A. Bargiela [4] which is a generalization and extension of the fuzzy Min-Max Neural network by Simpson. The GFMM method combine both learning methods such as supervised and unsupervised. This resultant algorithm can be used as pure clustering, pure classification, or hybrid clustering classification. Clusters and classes are represented by the hyperbox fuzzy sets as in original algorithm. Learning of network is very fast which can be completed in a few passes.
A General Reflex Fuzzy Min-Max (GRFMM) neural network which is capable to recognise the data by means

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of supervised, unsupervised and partially supervised learning [5]. It is not always possible to get a fully labelled dataset for training; hence partially supervised learning is more important. Both labelled and unlabelled data is learned by using previously acquired knowledge. The advantages of GRFMN are its ability to learn the data in a single pass through and retraining is not required while adding a new class or deleting an existing class.
Position and size of the hyperboxes which are generated during training decides the capability of Min-Max Classifier networks. An adaptive resolution min–max network [6] was proposed as a dual classifier model. Two algorithms, i.e., the adaptive resolution classifier (ARC) and pruned ARC, are developed. The hyperbox expansion process is not limited by a fixed maximum size, to overcome some of the undesired properties that occur in the original FMM model. The ARC network is less complex than FMM.
Bargiela et. al. [7] have proposed an inclusion/exclusion fuzzy hyperbox classifier. The inclusion and exclusion hyperboxes are created by the system. Input patterns which belong to the same class are contained by the inclusive hyperbox while the exclusion hyperboxes contain overlapped patterns. The training process from three step training process is reduced to only two step process because of the exclusive hyperbox.
A. V. Nandedkar et. al. have proposed the0 Fuzzy Min-Max Neural Network Classifier with Compensatory Neurons (FMMCNs). It is a supervised classification technique with new compensatory neuron architecture. The concept of Compensatory Neuron is inspired from human brain. FMCN eliminates use of process which based on minimal disturbance since it is found to be erroneous. The performance of FMMCNs is less dependent on the initialization of expansion coefficient, i.e., maximum hyperbox size.

A Fuzzy Min–Max Neural Network Based on Data Core (DCFMN) is proposed by Huaguang Zhang et. al [9]. It defines a new membership function for the neuron classification of DCFMN. This function considers the noise, the geometric centre of the hyperbox, and the data core are considered. DCFMN has strong robustness and high accuracy in classification.
To improve the performance of FMM classification process, when few numbers of large hyperboxes are formed in the network, some improvements are done by A. Quteishat et. al. [10]. When a new input pattern is provided, the target class is decided by Euclidean distance measure and also the fuzzy membership function of the input pattern is measured as in case of FMM. In this a rule extraction algorithm is also enclosed. For each FMM hyperbox a confidence factor which is measured from frequency of use is calculated, and a threshold which is user defined is used to prune the hyperboxes with low confidence factors.
Modified FMM with Genetic Algorithm (MFMM-GA) proposed in [11] which is a two stage classification of pattern and extraction of rule process is proposed by A. Quteishat et. al. Out of the two stage, in first consists of Modified Fuzzy Min-Max (MFMM) classifier and the second stage consists of classifier based on the genetic algorithm (GA). 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. In FMMGA pruning can been done to reduce the complexity.

III.PRUNING BASED ENHANCED FUZZY MIN-MAX NEURAL NETWORK

Enhanced Fuzzy Min-Max Neural Network has been proposed to improve the FMM learning algorithm and enhance its classification ability. EFMM network comprises the three heuristic rules that overcome the current limitations of the FMM learning algorithm, as follows:

- A new hyperbox expansion rule to minimize the overlapping regions of hyperboxes from different classes
- An extended hyperbox overlap test rule to identify all overlapping regions of hyperboxes from different classes
- A new hyperbox contraction rule to solve overlapping cases that are not covered by the existing contraction process.

A. 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 formulated, as follows:

$$\text{Max}_n(W_{ji}, a_{hi}) - \text{Min}_n(V_{ji}, a_{hi}) \leq \Theta.$$

Where, $a_h = (a_{h1}, a_{h2}, \ldots, a_{hn})$ is the input pattern
$v_j = (v_{j1}, v_{j2}, \ldots, v_{jn})$ and $w_j = (w_{j1}, w_{j2}, \ldots, w_{jn})$ are the minimum and maximum points of fuzzy set.
Θ is expansion coefficient

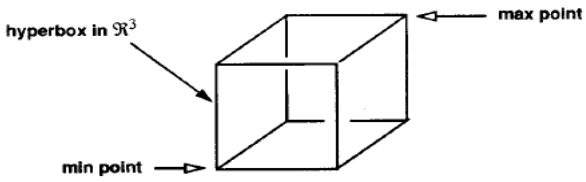

Fig 1. Hyperbox

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. During the expansion process, FMM computes the sum of all dimensions and checks the resulting score with ($nn\Theta$).

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.

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B. 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 area. When one of the following nine cases is met then an overlapping area exists.

Case 1:
$V_{ji}<V_{ki}<W_{ji}<W_{ki}$, $\delta^{new} = \min(W_{ji} - V_{ki}, \delta^{old})$.

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, $\delta^{old} - \delta^{new} = 1$.

C. 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.

Case1:
$V_{j\Delta} < V_{k\Delta} < W_{j\Delta} < W_{k\Delta}$, $W_{j\Delta}^{new} = W_{j\Delta}^{new} = \frac{W_{j\Delta}^{old} + V_{k\Delta}^{old}}{2}$

Case2:
$V_{k\Delta} < V_{j\Delta} < W_{k\Delta} < W_{j\Delta}$, $W_{k\Delta}^{new} = V_{j\Delta}^{new} = \frac{W_{k\Delta}^{old} + V_{j\Delta}^{old}}{2}$

Case3:
$V_{j\Delta} = V_{k\Delta} < W_{j\Delta} < W_{k\Delta}$, $V_{k\Delta}^{new} = W_{j\Delta}^{old}$

Case4:
$V_{j\Delta} < V_{k\Delta} < W_{j\Delta} = W_{k\Delta}$, $W_{j\Delta}^{new} = V_{k\Delta}^{old}$

Case5:
$V_{k\Delta} = V_{j\Delta} < W_{k\Delta} < W_{j\Delta}$, $V_{k\Delta}^{new} = W_{k\Delta}^{old}$

Case6:
$V_{k\Delta} < V_{j\Delta} < W_{k\Delta} = W_{j\Delta}$, $W_{k\Delta}^{new} = V_{j\Delta}^{old}$

Case7a:
$V_{j\Delta} < V_{k\Delta} \leq W_{k\Delta} < W_{j\Delta}$ and $(W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta})$,
$V_{j\Delta}^{new} = W_{k\Delta}^{old}$

Case7b:
$V_{j\Delta} < V_{k\Delta} \leq W_{k\Delta} < W_{j\Delta}$ and $(W_{k\Delta} - V_{j\Delta}) > (W_{j\Delta} - V_{k\Delta})$,
$W_{j\Delta}^{new} = V_{k\Delta}^{old}$

Case8a:
$V_{k\Delta} < V_{j\Delta} \leq W_{j\Delta} < W_{k\Delta}$ and
$(W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta})$, $W_{k\Delta}^{new} = V_{j\Delta}^{old}$

Case8b:
$V_{k\Delta} < V_{j\Delta} \leq W_{j\Delta} < W_{k\Delta}$ and
$(W_{k\Delta} - V_{j\Delta}) > (W_{j\Delta} - V_{k\Delta})$, $V_{k\Delta}^{new} = W_{j\Delta}^{old}$

Case9a:
$V_{j\Delta} = V_{k\Delta} < W_{j\Delta} = W_{k\Delta}$, $W_{j\Delta}^{new} = V_{k\Delta}^{new} = \frac{W_{j\Delta}^{old} + V_{k\Delta}^{old}}{2}$

Case 9b:
$V_{k\Delta} = V_{j\Delta} < W_{k\Delta} = W_{j\Delta}$, $W_{k\Delta}^{new} = V_{j\Delta}^{new} = \frac{W_{k\Delta}^{old} + V_{j\Delta}^{old}}{2}$

When the maximum point (Wj) of one or more dimension that belongs to a hyperbox (i.e., Hj) is enlarged and becomes totally overlapped with another hyperbox, (i.e., Hk), EFMM uses case 9(a) to perform contraction. Likewise, case 9(b) is applied when the minimum point (Vj) of one or more dimension that belongs to Hj is enlarged and becomes totally overlapped with Hk.

After the raining of EFMM, the pruning algorithm is applied to reduce the number of hyperboxes present. When there are less number of hyperboxes, the process will be faster. The concept of confidence factor is used for pruning. Based on the frequency of use and the prediction accuracy, the confidence factor is calculated. Confidence factor finds the hyperbox which are frequency used and the yield higher accuracy [12].

IV. EXPERIMENTAL RESULTS

The dataset used in this paper is the IRIS dataset. IRIS dataset is available freely and can be accessed from UCI machine learning repository. The IRIS dataset has 4 attributes and 3 classes. There are total 150 instances available to use. Each class contains 50 instances. For training dataset, prediction dataset and testing purpose the dataset is divided as per requirement. The EFMM neural network for learning and classification is implemented on data. To test the performance of EFMM and EFMM with pruning we have used Iris data set from UCI machine learning repository. For training of neural network 60%

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data is used, 20% data is used as the prediction set. Then for testing complete dataset is used.
To check the total number of hyperboxes formed, the value of expansion parameter is varied from 0.05 to 0.95. The sensitivity parameter for the membership function is set to 0.5. For pruning of hyperboxes the cut of value is set to 0.5 and weighing factor is set to 1.

TABLE III
COMPARISON OF NUMBER OF HYPERBOX FORMED

Expansion Coefficient (Θ)	No of Hyperboxes formed	
	EFMM	EFMM after Pruning
0.6	24	5
0.7	22	6
0.8	17	4
0.9	15	4

Table III shows the total number of hyperboxes formed when expansion coefficient is varied from 0.6, 0.7, 0.8 and 0.9.

TABLE IVV
COMPARISON OF RECOGNITION RATE

Expansion Coefficient (Θ)	Recognition Rate	
	EFMM	EFMM after Pruning
0.1	100	93.33
0.2	100	93.33
0.3	100	96.67
0.4	96.67	100
0.5	100	100
0.6	100	100
0.7	100	96.67
0.8	100	100
0.9	96.67	96.67

Table VIVII shows the recognition rate of EFMM and EFMM after pruning.

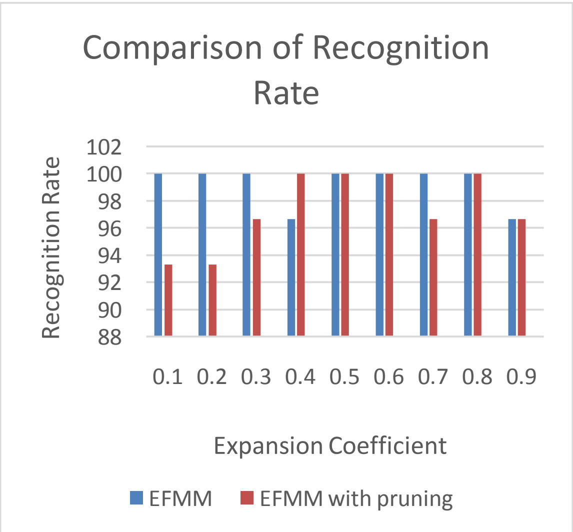

Fig. 1 shows the comparison of Recognition Rate of EFMM network and EFMM network after pruning

TABLE VIIIIXX
AVERAGE RECOGNITION RATE

Dataset	EFMM	EFMM after Pruning
IRIS	99.25± 1.7	97.7 ± 2.15

TableXIXIIXIII shows the average recognition rate of two algorithms

V. CONCLUSION

EFMM neural network is used for classification purpose. EFMM uses the concept of hyperbox for classification. There are total four steps followed in EFMM neural network with pruning. First, the hyperbox is expanded to contain the inputs. Overlap of hyperboxes is checked in second step. In third step contraction is done according to the overlaps. As the number of hyperboxes is more, the network complexity of EFMM in more. So, pruning of hyperboxes is done over EFMM neural network. Pruning of hyperboxes is done using the concept of confidence factor. The confidence factor of each hyperbox is based on its frequency of use and accuracy of prediction. As the number of hyperboxes reduced the network complexity of EFMM also reduces, but it affects the recognition ratio by small margin. The Average Recognition Rate after pruning is 97.7 ± 2.15.

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