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Different Pattern Classifier Techniques Based on Fuzzy Min-Max Neural Network

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Abstract: For classification of patterns, various neural networks related to Fuzzy Min-Max (FMM) have been studied. An Enhanced Fuzzy Min-Max (EFMM) neural network is most recent. EFMM Neural Network classifier that utilizes fuzzy sets as pattern classes has been studied. The contribution of EFMM is ability to overcome a number of limitations of the original FMM network and improve its classification performance. The key contributions are three heuristic rules to enhance the learning algorithm of FMM. First, a new hyperbox expansion rule to eliminate the overlapping problem during the hyperbox expansion process is suggested. Second, the existing hyperbox overlap test rule is extended to discover other possible overlapping cases. Third, a new hyperbox contraction rule to resolve possible overlapping cases is provided. A survey on Pattern Classification based on Fuzzy Min-Max Neural Network has been done and presented in this paper.

Keywords: ANN, MLP, FMM, EFMM, GFMM, ARC, MFMM.

I. INTRODUCTION

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

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.

In terms of ANN training, one of the main problems related to batch learning, such as in standard Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF), is catastrophic forgetting. Catastrophic forgetting is concerned with the inability of a learning system to remember what it has previously learned when new information is absorbed. The backpropagation ANN was found to create a new solution based on the most recent information only, when it was given two or more pieces of information to learn. This is obviously different from the functionality of our brain. The catastrophic forgetting problem is also addressed as the stability plasticity dilemma [2] & [3].

The dilemma addresses several 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. 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].

This paper is organised as follows. Various FMM related Neural Networks have been explained in section175. An enhanced Fuzzy Min-Max Neural Network and various hyperbox rules have been described in section 175. Finally conclusions are summarised in section 175.

II. FMM RELATED NETWORKS

A. Fuzzy Min-Max Neural Network

Simpson [3] suggested the fuzzy Min-Max network. This network is used to serve for supervised learning. For higher level of decision making a fuzzy set approach to pattern classification is used. The 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.

B. General Fuzzy Min-Max Neural Network

A general fuzzy Min-Max(GFMM) neural network developed by B. Gabrys and A. Bargiela [4] which is a

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generalization and extension of the fuzzy Min-Max clustering and classification algorithms developed by Simpson. The GFMM method combines the supervised and unsupervised learning within a single training algorithm. The fusion of clustering and classification resulted in an algorithm that can be used as pure clustering, pure classification, or hybrid clustering classification. This hybrid system exhibits an interesting property of finding decision boundaries between classes while clustering patterns that cannot be said to belong to any of existing classes. Similarly to the original algorithms, the hyperbox fuzzy sets are used as a representation of clusters and classes. Learning is usually completed in a few passes through the data and consists of placing and adjusting the hyperboxes in the pattern space which is referred to as an expansion–contraction process. . The classification results can be crisp or fuzzy. New data can be included without the need for retraining. While retaining all the interesting features of the original algorithms, a number of modifications to their definition have been made in order to accommodate fuzzy input patterns in the form of lower and upper bounds, combine the supervised and unsupervised learning, and improve the effectiveness of operations.

C. General Reflex Fuzzy Min-Max Neural network

A General Reflex Fuzzy Min-Max Neural Network which is capable to extract the underlying structure of the data by means of supervised, unsupervised and partially supervised learning has been presented in [5]. Learning under partial supervision is of high importance for the practical implementation of pattern recognition systems, as it may not be always feasible to get a fully labelled dataset for training or cost of labelling all samples is not affordable. GRFMN applies the acquired knowledge to learn a mixture of labelled and unlabelled data. It uses aggregation of hyperbox fuzzy sets to represent a class or cluster. A novel reflex mechanism inspired from human brain is used to solve the problem of class overlaps. The reflex mechanism consists of compensatory neurons which become active if the test data belongs to an overlap region of two or more hyperboxes representing different classes.

These neurons help to approximate the complex topology of data in a better way. The proposed new learning approach to deal with partially labelled data and inclusion of compensatory neurons, has improved the performance of GRFMN significantly. The advantages of GRFMN are its ability to learn the data in a single pass through and no requirement of retraining while adding a new class or deleting an existing class.

D. Adaptive resolution Min-Max classifier

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. 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 devised. The hyperbox expansion process is not limited by a fixed maximum size, to overcome some of the undesired properties in the original FMM model. The network structure is also less complex as compared with FMM.

E. Inclusive/Exclusive Fuzzy Network

Bargiela et. al. [7] have proposed an inclusion/exclusion fuzzy hyperbox classifier. This model creates two types of hyperboxes, i.e., the inclusion and exclusion hyperboxes. The inclusion hyperboxes are used to contain input patterns from the same class. Other overlapped patterns are contained by the exclusion hyperboxes. The use of the exclusion hyperboxes reduces the training process from three steps (expansion, overlap test, and contraction) to two steps (expansion and overlap test). This is achieved through a contentious area of the pattern space to approximate the complex data topology, which helps to solve the overlapping problem in FMM.

F. Fuzzy Min-Max Neural Network Classifier with Compensatory Neuron Architecture

A Fuzzy Min-Max Neural Network Classifier with Compensatory Neurons (FMCNs) uses hyperbox fuzzy sets to represent the pattern classes [8]. It is a supervised classification technique with new compensatory neuron architecture. The concept of Compensatory Neuron is inspired from the reflex system of human brain which takes over the control in hazardous conditions. Compensatory Neurons (CNs) imitate this behaviour by getting activated whenever a test sample falls in the overlapped regions amongst different classes. These neurons arecapable to handle the hyperbox overlap and containment more efficiently. Simpson [3] used contraction process based on the principle of minimal disturbance, to solve the problem of hyperbox overlaps. FMCN eliminates use of this process since it is found to be erroneous. FMCN is capable to learn the data online in a single pass through with reduced classification and gradation errors. One of the good features of FMCN is that its performance is less dependent on the initialization of expansion coefficient, i.e., maximum hyperbox size.

G. Data-Core-Based Fuzzy Min–Max Neural Network for Pattern Classification

A Fuzzy Min–Max Neural Network Based on Data Core (DCFMN) is proposed by Huaguang Zhang et. al [9]. A new membership function for classifying the neuron of DCFMN is defined in which the noise, the geometric centre of the hyperbox, and the data core are considered. Instead of using the contraction process of the FMNN described by Simpson [3], a kind of overlapped neuron with new membership function based on the data core is proposed and added to neural network to represent the overlapping area of hyperboxes belonging to different classes. Furthermore, some algorithms of online learning and classification are presented according to the structure of DCFMN. DCFMN has strong robustness and high accuracy in classification taking onto account the effect of data core and noise. The performance of DCFMN is checked by some benchmark datasets and compared with some traditional fuzzy neural networks, such as the fuzzy Min-Max neural network (FMNN), the general FMNN, and the FMNN with compensatory neuron.

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H. Modified FMM (MFMM):
In attempt to improve the classification performance of FMM when few numbers of large hyperboxes are formed in the network, some modifications are done by A. Quteishat and C. P. Lim [10]. 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 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.

I. Modified FMM with Genetic Algorithm (MFMM-GA):
Modified FMM with Genetic Algorithm (MFMM-GA) proposed in [11] is 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 FMMGA 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.

J. Offline and Online FMM-CART:
A new approach to classify and detect faults using a hybrid fuzzy Min-Max (FMM) neural network and classification and regression tree has been proposed in [12] [13]. It 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.

III. 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:

1. A new hyperbox expansion rule to minimize the overlapping regions of hyperboxes from different classes
2. An extended hyperbox overlap test rule to identify all overlapping regions of hyperboxes from different classes
3. 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:

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

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. A 3-D hyperbox is shown in fig. 1.
Θ is expansion coefficient

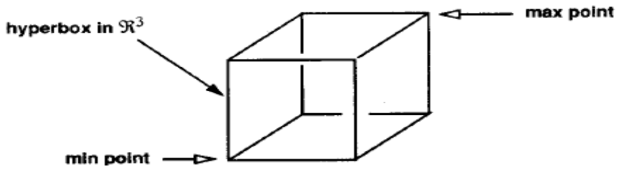

Fig. 1 A 3-D Hyperbox with Minimum and Maximum Points

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 ($n^2\Theta$).
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.

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:
$V_{ki} < V_{ji} \le W_{ji} < W_{ki}$
$\delta^{new} = \min(\min(W_{ji} - V_{ki}, W_{ki} - V_{ji}), \delta^{old})$.
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:
$V_{j\Delta} < V_{k\Delta} \le W_{k\Delta} < W_{j\Delta}$ and $(W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta})$, $V_{j\Delta}^{new} = W_{k\Delta}^{old}$
Case7b:
$V_{j\Delta} < V_{k\Delta} \le W_{k\Delta} < W_{j\Delta}$ and $(W_{k\Delta} - V_{j\Delta}) > (W_{j\Delta} - V_{k\Delta})$, $W_{j\Delta}^{new} = V_{k\Delta}^{old}$
Case8a:
$V_{k\Delta} < V_{j\Delta} \le W_{j\Delta} < W_{k\Delta}$ and
$(W_{k\Delta} - V_{j\Delta}) < (W_{j\Delta} - V_{k\Delta})$, $W_{k\Delta}^{new} = V_{j\Delta}^{old}$
Case8b:
$V_{k\Delta} < V_{j\Delta} \le W_{j\Delta} < W_{k\Delta}$ 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.

IV. 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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