M-FMCN: Modified Fuzzy Min-Max Classifier Using Compensatory Neurons

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Abstract: - A new fuzzy Min-Max classifier is proposed that uses modified compensatory neurons. The proposed classifier is online, single-pass and supervised method that is based on fuzzy Min-Max neural network classifier with compensatory neurons. In this method for handling overlapping regions that mainly are created in borders, a modified compensatory nod with a radios-based transition function is used which increases the classification accuracy in discriminating cases. On contract of modifications in the structure of the algorithm, time and space complexity of the algorithm has been decreased and experimental results show that the proposed method is less sensitive to external parameters that are provided by user.

Key-Words: - Neural network, Fuzzy, Min-Max Classifier, Classification, Clustering, Hyperbox.

1 Introduction
Fuzzy logic was first proposed by professor Zadeh[1] that due to consistency of its rules with the real world and its importance and high performance in pattern recognition, fuzzy logic is used widely in pattern recognition field[2]. In many cases, fuzzy logic is combined with other pattern recognition tools to make use of its power in uncertainty. Neuro-fuzzy is one of these methods and is the combination of fuzzy logic and artificial neural networks [3-5]. Neuro-fuzzy networks due to high recognition rate of fuzzy systems and high computational performance of neural networks is a powerful tool in pattern recognition [6-8].

Fuzzy Min-Max is a specific type of neuro-fuzzy that has high efficiency rather than other machine learning methods [9] and its learning phase is single pass through and online adaptive that is done in a very short time. These networks are used for classification and clustering, and for this purpose, "hyperbox" concept is used. Each hyperbox is a convex box that specifies a small part of pattern space and we save it only by two vertices V and W that are respectively corresponding min and max points of the same hyperbox. Every hyperbox belongs to a class and its corresponding space belongs to the same class too [10]. Hyperboxes are expanded during the training phase till almost the whole pattern space is covered, but at the end of this phase, there should not be any overlap between Hyperboxes that belong to different classes. Maximum extension of these boxes controlled with $\theta$ coefficient that is initialized by user.

Early methods of FMM [7, 10] used contraction process to eliminate overlaps, but this type of overlap handling had an undesirable effect on performance of these networks and newer methods [6, 8, 12, 13] used special nodes similar to regular hyperboxes to manage these regions. Transition function (membership function) of these nodes determines how to classify samples in the overlap region. These methods have better performance than previous methods. The most prominent of them is FMCN [8] method that was proposed by Nandedkar and Biswas in 2007 and has higher performance then similar methods. This method uses two kind of compensatory nodes (OCN and CCN) to handle overlap problem. Yet some structural problems are available in the network and membership functions are not optimal.

2 Background and Similar works
Many methods have been proposed in FMM domain and in this section we survey most important of these methods, their evolution, and explain the advantages and disadvantages of each of them [7, 8, 10, 13-24].
2.1 Fuzzy Min-Max Classification Neural Networks (FMM)

FMM is a machine learning method that has been proposed by Simpson in 1992 [10] and it can be used for classification or clustering purposes. For this purpose, Hyperbox concept is used where hyperbox is a convex box that its covered space is determined by V and W. These points are respectively min and max points of hyperbox as shown in Figure 1. Each Hyperbox belongs to one class and covers a range of pattern space.

![Figure 1: A 3D hyperbox and its min-max points](image)

These boxes are created and adjusted during training phase, and in test phase these boxes and their membership functions are used to assign an input sample to a class and classify them [10].

FMM neural network is composed of three layers where the first layer belongs to inputs (FA), the second layer represents (FB) Hyperboxes and each node in the third layer (FC) represents a class, also each hyperbox is a node of middle layer (FB) and membership function of this hyperbox is transition function of that node [7, 10].

All hyperboxes are created and adjusted during the training phase. For each sample $A_h$, it is checked if this sample is located inside any of boxes or not, if there is no such hyperbox, the next three steps are executed respectively.

i. Expansion: Hyperboxes are created or expanded

ii. Overlap test: Overlap between hyperboxes is determined.

iii. Contraction: Overlaps eliminated using contraction.

2.2 GFMM (General Fuzzy Min-Max Neural Network)

This method was proposed by Gabrys and Bargiela in 2000 [7] and proposed good changes in FMM to improve accuracy. Important changes done in this method are:

1) Input patterns can be fuzzy hyperboxes or crisp-points in the pattern space.

2) The fuzzy hyperbox membership function and basic hyperbox expansion constraint proposed in FMM have been changed.

3) The labeled and unlabeled input patterns can be processed at the same time which results in an algorithm that can be used as pure clustering, pure classification, or hybrid clustering or classification system.

4) The parameter regulating the maximum hyperbox size can be changed adaptively in the course of GFMM neural network training.

2.3 EFC (inclusion/exclusion fuzzy hyperbox classifier)

This method is proposed by Bargiela et al. in 2004 [6]. In this method a few changes have been made in training process to overcome overlapped regions problem. Unlike previous scheme in this method, contraction is not used to eliminate overlaps.

Solution of this method to handle overlap region problem is to use a combination of exclusion and inclusion hyperbox sets to approximate the complex topology of the data. Exclusion boxes are similar to ordinary Hyperboxes and each of them represents an overlapped [6]. Inclusion hyperboxes represent data that belongs to a class and exclusion hyperboxes represent overlapped areas and are assigned to class $C+1$ ($C$ is the number of classes) and samples that are contained in these boxes represent class $C+1$.

2.4 FMCN (Fuzzy Min-Max Neural Network Classifier with Compensatory Neurons)

This method was proposed by Nandedkar and Biswas in 2007[8] and unlike previous methods has a good solution for handling overlapped area problem. In this method overlapped regions are handled by compensation nodes (CNs) that are similar to exclusion nodes in EFC and are divided into OCN (Overlap Compensation Neuron) and CCN (Containment Compensation Neuron) groups. First group is used to handle simpler overlap and the second group is used to handle overlaps that one box fully or partially is contained in another box [8].

Result of implementation of FMCN shows that this method is more efficient than previous methods but has some disadvantages that can be summarized in the following points.

![Figure 5: FMCN membership function for compensatory nodes](image)
b) In this method whenever one hyperbox is expanded, overlap of this hyperbox and all other boxes that belong to other classes is checked and if any overlap exists, a compensatory node is added to the network. Therefore duplicate nodes can be created.
c) In this method if a created box (that only contains one point) is in another hyperbox that belong to another class and the created box won’t expand in next step, there will be an overlap that this algorithm won’t eliminate it.

Like previous methods, this method doesn’t have 100% classification accuracy over training set. But note that despite above points, FMCN is one of the best FMM-based methods [8].

3 Proposed Method
This method is based on the FMCN [8] but some changes done in structure and training phase. Changes done in the structure address time and space complexity and reduce both of them. Some changes are done in the testing phase; these changes include membership function of compensatory nodes that increases classification accuracy.

2.3 Training Phase
In this phase, the structure of the network is shaped and different parts of it are created. Like other methods based on FMM, required hyperboxes are created in this phase and are used to handle overlapping regions. For this purpose, compensatory nodes are used like those in FMCN but the difference is that in FMCN, compensatory nodes are added to handle overlapping regions right after expansion of each hyperbox but in the proposed method, handling overlapping regions is done after expansion of all hyperboxes. This delayed handling of overlapping regions reduces needed operations and therefore decreases time complexity.

The training phase has two steps that are: creation and adjustment of hyperboxes; and handling overlapping regions. In the first section, for each sample, expansion is done to create and adjust hyperboxes. After the first section, handling of overlapping regions is done. In the second section, overlaps between hyperboxes are identified and for each overlap one node is added in OCN or CCN. Figure 7 shows flowchart of the training phase.

2.3 Testing Phase
In this phase hyperboxes and compensatory nodes created in the training phase and membership functions of these hyperboxes and nodes are used to do the classification task. As mentioned, one of the problems of FMCN is using improper membership functions specially functions used in OCN nodes. In Figure 5 decision making in these functions is shown. To find the best membership function for OCN nodes, 4000 overlapping regions which were selected randomly and were created over standard datasets selected. Statistical analysis shows that 55% of samples in these regions are member of the class that the sample is closer to center of its hyperbox. This shows that using distance-based or radius-based functions are a good choice to handle these regions. To make use of this analysis the Equation (1) is used as membership function of nodes in OCN.

\[ d_{sp} = \frac{W_j - m_p}{A_b} \cdot \left( \frac{(W_j - V_j)}{2} \right) \]  

Where \( W_j \) and \( V_j \) are max and min points of the overlapping area, \( m_p \) is the center of the hyperbox \( p \) and \( A_b \) is input sample.

Figure 8 shows classification in overlap regions in M-FMCN.

In Figure 8 classification procedure is shown for different possible cases. As regards to the classification procedure in overlapping regions, we expect higher classification accuracy than previous methods.

4 Experimental Results
In this section obtained results of the proposed method (MFMCN) is compared with other FMM-based methods investigated in [6-8, 10]. To evaluate these methods, standard datasets which are available over internet like Breast Cancer, Glass, Wine and Iris [25] are used. Additionally, two more datasets, a circle with radius 9.5 and an exponential function are used in a 21*21 matrix that are show in Figure 9.

In the remaining of the paper, 50% of data is randomly selected for training and the rest of data is used to test methods.

4.1 Classification Accuracy
Misclassification rate is one of the most important parameters to compare classifiers. In this section classification accuracy of FMM-based methods is investigated for different values of $\theta$. Results are shown in Figures 10-13.

Classification accuracy in non-separable cases does not increase too much in compared with other FMM-based methods, but in separable cases like Circle and Exponential datasets, there will be a great increase in accuracy. In some cases, like Figure 12, FMCN has a better performance and it is because of type of distribution of samples in the Iris dataset.

4.2 Space Complexity
A measurement for space complexity can be number of created hyperboxes and nodes, because these hyperboxes and nodes are created during the training phase and should be used in the testing phase, therefore they should be saved and have a space cost.
4.3 Time Complexity

In the hyperbox creation phase, both methods have the same time and space complexity, but the difference is in how they handle overlap regions. In FMCN after each adjustment in size of a hyperbox in CLN, nodes in OCN and CCN are updated but in the proposed method after adjusting all hyperboxes in CLN, these nodes are updated. Therefore the time complexity of the proposed method is less than FMCN.

Results of running mentioned methods are shown in Figures 18-20. These graphs are results of running classifiers on a 1.3 MHz core2 duo with 4G RAM. Note that GFMM, because of its strategy of handling overlap regions has a high time complexity and its results are not comparable to other methods So, GFMM is not shown.

5 Conclusions

FMCN has some disadvantages, in this paper we investigated them and proposed a method to improve it. First some changes are made in the structure of FMCN to decrease time and space complexity. The new structure prevents from creating and saving useless hyperboxes during the training phase which leads to a faster classifier. To improve classification accuracy, some changes are made in the membership functions of nodes used to handle overlap regions. Using statistical analytics, found a better membership function for these nodes that increases accuracy in the border lines especially for separable cases. Experimental results show that the proposed method has a better performance and accuracy in compared with other FMM-based methods. This research shows that some changes in FMM networks can improve their performance and accuracy. Still better membership functions can improve accuracy of the network in border line of
classes. Other classifiers can be combined with this classifier in overlap regions to improve accuracy.

References: