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Survey on Fuzzy Min-Max Neural Network Classification

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Abstract: Fuzzy min max (FMM) model is a combination of both fuzzy set and neural network for classification. It uses hyperbox structure for pattern classification which consists of min and max points of opposite corners of hyperbox. To handle overlapping region of hyperboxes during classification is a crucial role. There are various FMM models are described in which during learning phase the hyperboxes are expanded until almost the whole pattern space is covered. At the end of learning phase, there are no overlapping hyperboxes that belong to different classes. The maximum expansion of these hyperboxes is controlled by the expansion parameter θ which is used for expansion.

Keywords: Fuzzy min-max (FMM) model, hyperbox, neural network, pattern Classification.

I. INTRODUCTION

Fuzzy logic is an engineering and data analysis approach proposed by Lotfi A. Zadeh [8]. Fuzzy logic is derived from fuzzy set theory dealing with reasoning that is approximate rather than precisely deduce from classical two-valued logic. So, fuzzy logic is a method to formalize the human capacity of imprecise reasoning. Such reasoning represents the human ability to reason approximately and judge under uncertainty [8]. Fuzzy set theory has long been considered a suitable framework for pattern recognition, especially classification procedures because of the inherent fuzziness involved in the definition of a class or of a cluster [3]. An Artificial Neural Network (ANN) is a paradigm for information processing. Their functions are similar to that of biological nervous systems, such as the brain process information. Nowadays, ANNs are used in different fields, e.g., power systems, healthcare and fault detection and so on [5], [11], [12], [14], [16], [25]. Pattern classification is one of the active ANN application domains [23]. Neuro-fuzzy systems are created by combining fuzzy logic and artificial neural networks. Their connections have numeric weights so that it can be tuned based on experience, making the neural network adaptable for inputs and therefore they becomes capable of learning.

There are two important training strategies for pattern classification: supervised learning and unsupervised learning. In supervised learning, class labels are provided already with input patterns and the decision boundary between classes that minimizes misclassification is sought. In unsupervised learning, also called as a cluster analysis problem, the training pattern data is unlabelled. So, it becomes necessary to deal with the task of splitting a set of patterns into a number of more or less homogenous clusters [6] with corresponding to a suitable similarity measure used. The characteristic of human reasoning is the ease with of coping with uncertain or ambiguous data to handle in real life. The classical statistical approaches to pattern classification have been found inadequate in these situations. To overcome this problem required a search for a more flexible label in classification problems. Therefore, combination of both fuzzy set and neural network is used in various domain [12], [15], [25]. Section I describes introduction about Neuro-fuzzy system classification, section II describes literature survey and section III includes conclusion.

II. LITERATURE SURVEY

There are various method have been developed in FMM based model [1], [4], [6], [7], [10]. Fuzzy Min-Max Neural Network Classification was the method which was developed in 1992 [9]. This basic FMM model is as follows:

Fuzzy min-max (FMM) neural network is a special type of a neurofuzzy system mostly used in domain [17], [18], [21], [22], [23], [25] which has high efficiency compared to the other machine learning methods [10]. Fuzzy Min-Max Classification technique was developed in 1992 [9]. The fuzzy Min-Max classification neural networks are built using hyperbox fuzzy sets. A hyperbox is defined by a region in R^n, as shown in fig. 1. More specifically it is in region $[0\ 1]^n$, because the data is normalized in between 0 and 1 and all patterns contained within the hyperbox have full class membership. A hyperbox B is fully defined by its minimum V and maximum W vertices. So that, $B = [V, W]\ [0\ 1]^n$ with $V,W \in [0\ 1]^n$. Fuzzy hyperbox B is described by a membership function or transition function, it then maps the universe of discourse (X) into a unit interval. The hyperboxes are convex boxes in the pattern space. Each hyperbox in the pattern space is determined by V_j and W_j points [9]. They are used to for the purpose of representation of min and max points of the hyperbox. Each hyperbox is used to one of the classes and covers that particular part of pattern space. These V_j and W_j are the min and max corners of the hyperbox as shown in fig. 1.

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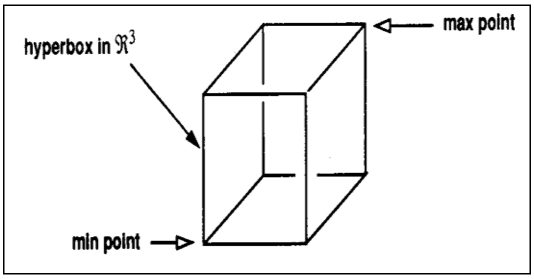

Fig. 1. Example of Hyperbox Structure [9]

Membership function defines the fuzziness in a fuzzy set irrespective of element in the set, which may be discrete or continuous. The membership functions are generally represented in a graphical form. There are some limitations for the shapes which are used to represent graphical structure of these membership functions. The rules that describe fuzziness graphically are also fuzzy. The membership function defines all the information contained in that fuzzy set [26]. As all information in a fuzzy set is represented by its membership function, it is useful to develop a lexicon of terms to represent various special features of this function. These membership functions are varying according to different types of FMM model used.

The membership function is defined formally as B(x) that represents a degree of membership which describes an extent to which x belongs to *B*. If B(x) =1 then, x fully belongs to *B*. If *B*(x) is equal to zero, *x* is fully excluded from *B*. The values of the membership function that are in between 0 and 1 represent a partial membership relation of x and B [26]. As the higher the membership grade, the stronger is the association of the given element to B. The hyperbox fuzzy set can then be denoted as B = X, V, W, b(X, V, W). Here, X is an input pattern that in general represents a class labelled hyperbox in $[0\ 1]^n$ and n is the number of dimensions used in their membership function calculation [9]. Each class may have one or more hyperbox(es). Various membership functions may be used for creation of these hyperboxes. There are following three steps are followed in basic fuzzy min max neural network classification [9].

In Fig. 2, it shows classical structure of FMM neural networks model.

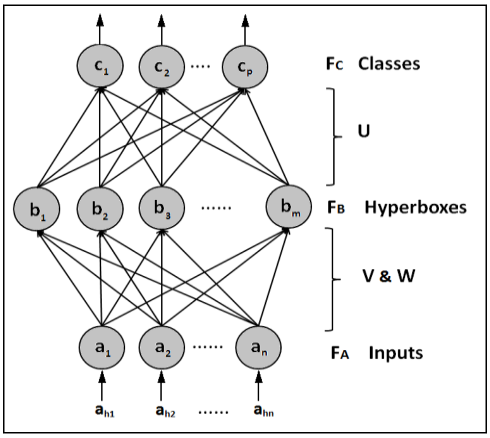

Fig. 2. Classical structure of FMM model [9]

It consists of three layers where the first layer belongs to inputs (F_A), the second layer represents hyperboxes (F_B), and each node in the third layer represents a class (F_C). Each hyperbox is a node of middle layer (F_B), and the membership function of this hyperbox is the transition function of the same node. Each node of F_A layer is connected to all nodes in the F_B layer and each of these links has two weights (V_{ij} and W_{ij}). These are the min and max points of the B_j hyperbox respectively. Here, i is the index of the nodes in the first layer.

Each node of the middle layer is also connected to all nodes in the F_C layer. Output of F_C layer provides particular class.

A. *Expansion:*

In this expansion step, when any sample is presented, a hyperbox must be found to present the same class and also be capable of expansion to cover the sample and the hyperbox size does not exceed the threshold parameter. If there is no such hyperbox is found then a new hyperbox is created with min and max points equal to the corresponding data points.

B. *Overlap Test:*

In this step, the overlapping area of the expanded hyperbox is verified against all hyperboxes that belong to the other classes. To eliminate this overlap, the portion that has least overlap is used for contraction purpose.

C. *Contraction:*

In this contraction step, if there is no any overlap, it is not executed. Otherwise, it considers the type of the overlap in the selected dimension of overlap test direction. All these steps are executed on every learning sample to create and adjust the hyperboxes. The essential point in FMM model is the maximum size of hyperboxes expansion parameter (θ). It is the most important parameter that bounds the number of created hyperboxes. As the larger the value of (θ), there are fewer hyperboxes created, and that network will be more traceable but the overlapping region increases. This leads to lower precision of the algorithm. Therefore, there is a trade-off between accuracy and traceability of these networks [10].

For FMM method it uses Simpson's function [9]. It is defined as follows:

$$b_j(A_h) = 1/2 \sum [\max(0, 1 - \max(0, \gamma \min(1, a_{hi} - w_{ji}))) + \max(0, 1 - \max(0, \gamma \min(1, v_{ji} - a_{hi})))] \qquad (1)$$

where, $A_h=(a_{h1}, a_{h2}, ..., a_{hn}) \in I\,n$ is the h^{th} sample and γ is a coefficient between 0 and 1 that regulates how fast the membership values decrease as the distance between A_h and B_j increases [9]. All hyperboxes are created and adjusted in the learning phase. It uses hyperboxes that are made up with convex boxes in the pattern space. Each hyperbox in the pattern space is determined by its min and max points in the pattern space. The three steps described above are executed for every learning sample to create hyperbox and to adjust required hyperboxes accordingly.

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The size of a hyperbox is controlled by parameter (θ), which varies between 0 and 1. When the value of (θ) is small, more hyperboxes are created. When (θ) is large, the number of hyperboxes is small, and the membership function values are high. A large number of hyperboxes may end up with the same value of membership function (e.g., unity) [5]. The value of increase in expansion parameter (θ) leads to lower precision of the algorithm. This method, only gives improvement in the classification results when (θ) is large.

General Fuzzy Min-Max Neural Network (GFMM) was developed by Gabrys and Bargiela in 2000 [6]. This method combines the supervised and unsupervised learning within a single training algorithm. This method added some changes in the basic FMM model to improve efficiency. Different membership function was introduced. The extension introduced in the GFMM specification was the form of the input patterns that can be processed. The parameter which regulates the maximum hyperbox size can be changed adaptively, at the time of GFMM neural network training phase. This method can handle processing of labeled and unlabeled input patterns at the same time. Therefore, it could be used for pure clustering, pure classification, or hybrid clustering/classification [10]. In contrast to the classical FMM model, the GFMM algorithm defines some constraint which regulates the maximum size of the hyperbox so as to control the size of the hyperbox for each of the dimension [6]. Therefore, it is possible ensure that the difference between max and min value for each dimension will not be greater than the user specified value. The GFMM method produces considerably fewer hyperboxes than the classic FMM classification and also gives fewer misclassifications than previous methods. The training of the GFMM neural network is very fast and, as long as there are no identical data belonging to two different classes. It allows processing of both fuzzy and crisp input patterns. Since the GFMM forms the decision boundaries by covering the pattern space with hyperboxes, its performance will deteriorate when the characteristics of the training and test data will be very different [6].

Inclusion/Exclusion Fuzzy Hyperbox Classification was proposed by [2]. There are some changes have been made in the learning process to overcome the overlapping areas problem. Unlike previous method, this method does not use contraction to eliminate overlaps. It eliminates some unnecessary parts of hyperboxes, which causes reduction in the efficiency. It is similar to GFMM, it generates two types of hyperboxes. The first type of hyperbox is called inclusion hyperboxes, it is the type of hyperboxes that have considered in FMM model. The second type is called exclusion hyperboxes that represent hyperboxes which contain data belonging to different classes. Inclusion hyperboxes represent data that belongs to same class, and exclusion hyperboxes represent overlapped areas and are assigned to class p + 1 (p is the number of classes) [10]. So, the exclusion hyperboxes represent areas of the pattern space in which the classification task is ambiguous. In this method, if the new exclusion hyperbox contains any of the previously identified exclusion hyperboxes, the included hyperboxes are eliminated from the set of exclusion boxes. By using these, it is possible to represent complex topologies with a reduced number of hyperboxes [2]. The low misclassification rate and good interpretability of the results of this method is obtained in this method. But, it rejects a proportion of patterns that fall into the exclusion hyperbox set. If this proportion is small then this method provides an optimum mix of good classifier features. However, if the exclusion set becomes comparable in size to the inclusion set the maximum size of hyperboxes needs to be reduced [2].

Fuzzy Min-Max Neural Network Classifier with Compensatory Neuron (FMCN) was developed by Nandedkar and Biswas [4]. FMCN uses hyperbox fuzzy sets to represent the pattern classes. 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 [4]. The performance of FMCN is almost independent of the expansion parameter (θ) maximum hyperbox size. The (Compensatory Neuron) CNs are divided into overlap compensation neuron (OCN) and containment compensation neuron (CCN) groups. The OCN is used to handle simpler overlaps. The CCN group is used to handle overlaps where one box fully or partially is contained in another box. It creates CNs dynamically during learning process. These CNs maintain the hyperbox dimension and control the membership in the overlapped region and increases robustness in pattern classification. Compensatory nodes only have output in particular overlapped region, but they do not have influence on classification result in region other than overlapped area. The output of the classifying neurons is connected to a class node to which that neuron or hyperbox belongs. Similarly the output of the compensatory neurons is connected to a class node, which needs the compensation [4]. FMCN shows that the method is more efficient than the previous methods [4] but has some disadvantages like, This FMCN does not use appropriate membership function for compensatory boxes, so it cannot classify correctly high percentage of samples that are present in overlapped regions. As compared to previous methods, this method does not have 100% classification accuracy over the training set [4].

A Granular Reflex Fuzzy Min-Max Neural Network for Classification (GrRFMN) was developed by A. V. Nandedkar and P. K. Biswas [27]. In this method, granular neural network (GNN) called as granular reflex fuzzy min–max neural network (GrRFMN) is used. It can learn and classify granular data. It uses hyperbox fuzzy set to represent granular data**.** Here, the network can be trained online using granular or point data. The activation functions of neurons are designed to tackle data of different size. As compared to FMCN architecture, GrRFMN has 2n input nodes, so it becomes capable to process granules in the form of hyperboxes. Thus, the requirement of double connections between input and hyperbox nodes in FMCN [4] is avoided in GrRFMN. Like FMCN, the compensatory neurons in GrRFMN are activated only when the input granule completely falls in the overlap zone represented by them. If the input data is in a point form, then GrRFMN functioning converges to FMCN [27]. It enables a trained GrRFMN to classify granules of different sizes more correctly than GFMM. Therefore, the performance of this method is better than previous method. But, Granularity of this architecture decreases as the value of expansion parameter (θ) increases from 0 to 1.

Data-Core-Based Fuzzy Min-Max Neural Network (DCFMN) was developed Zhang [7]. It uses data core and geometry centre for classifying the field data accurately. Data core is the mean value of all data points in the same hyperbox, whereas geometry centre is the centre of the hyperbox. As compared to the membership function of GFMN and FMCN, the membership function in the DCFMN considers the characteristics of the data and impact of noise at the same time. The expansion method used in DCFMN can reduce the number of hyperboxes in the network. In this method, the hyperbox overlap test is begun after creating and expanding hyperboxes for all the training data. DCFMN contains two classes of neurons: classifying neurons (CNs) that are used to classify the patterns of data and overlapping neurons (OLNs) that are used for handling all kinds of overlap in different hyperboxes, which is different from FMCN [4]. Unlike FMCN, only one kind of OLN is required in case of DCFMN to handle all kinds of overlapping hyperboxes. If the expansion coefficient of the hyperbox in the DCFMN is the same as that of FMCN, the number of hyperboxes in DCFMN is less than FMCN [4], [7]. The performance of DCFMN is better than the others. But when the expansion coefficient is larger than 0.7 [7], the accuracy of all the methods becomes worse than before because there is only a small number of hyperboxes in FMNN, GFMN, and DCFMN. DCFMN has strong robustness and high accuracy in classification taking onto account the effect of data core and noise [7]. On the other hand, performance of FMCN is better than the other methods when the expansion coefficient is larger than 0.7, because the hyperbox in FMCN cannot be expanded when it overlaps with any previous hyperbox of different classes, which causes larger number of hyperboxes than other methods [4], [7]. The membership function of CNs considers the noise, geometric centre of the hyperbox, still DCFMN cannot correctly classify high percentage of samples that are located in the overlapped regions, and cannot classify all learning samples correctly either.

Multi-Level Fuzzy Min-Max Neural Network Classification (MLF) [10] uses multilevel structure to classify patterns. It uses smaller hyperboxes with different levels for classification. It is developed to handle overlapping region problems in classical FMM models.

MLF method is capable for learning nonlinear boundaries. It is processed with a single pass through the data and uses different classifiers at levels. By using separate classifier it gives output of the network which is formed by combining the outputs from these classifiers. As compared to other classic FMM methods, the contraction step is not used to handle the overlap problem in this method. Hyperboxes of the latter levels are smaller and are more precise than hyperboxes of earlier levels.

Hence, in this method the patterns which belong to overlapped regions can be classified more precisely in the next level of the network by different classifiers which are used. This method is not sensitive to size of the overlapped area. Hence, misclassification is not too much. Child nodes in MLF generally have smaller hyperboxes than those of parent nodes. So, boundary regions have classification with a great accuracy in the MLF method. As compared to other classic FMM model it has faster training phase in most of the cases. Also, the recognition rate for training samples is 100% in MLF method [10]. Therefore, it gives better result than other classic FMM models. As compared to other method MLF is used for problems with eccentric and nonlinear boundaries. Therefore, it can be used in real time application.

III. CONCLUSION

There are various FMM based neural network classification techniques. These method uses hyperbox structure to classify patterns. FMM, FMCN, GFMM do not classify the pattern space correctly in overlapped region. There is a trade-off between accuracy and traceability of these networks. In MLF based neural network classification, it can classify overlapped area of hyperboxes more correctly than previous methods. As child nodes in MLF generally have smaller hyperboxes than those of parent nodes, it can classify more precisely in the next level. So, boundary regions have classification with a great accuracy in the MLF method. On the account of MLF's high performance and accuracy, it can be used in various applications such as classification problems with irregular and nonlinear boundaries.

REFERENCES

[1] A. Bargiela, W. Pedrycz, and M. Tanaka, "Exclusion/inclusion fuzzy classification network," in Knowledge-Based Intelligent Information and Engineering Systems. New York, USA: Springer-Verlag, pp. 1236–1241, 2003.

[2] A. Bargiela, W. Pedrycz, and M. Tanaka, "An inclusion/exclusion fuzzy hyperbox classifier," Int. J. Knowl. Based Intell. Eng. Syst., vol. 8, no. 2, pp. 91–98, 2004.

[3] A. Joshi, N. Ramakrishman, E. N. Houstis, and J. R. Rice, "On Neuro biological, neuro-fuzzy, machine learning, and statistical pattern recognition techniques," IEEE Trans. Neural Network, vol. 8, no. 1, pp. 18–31, Jan. 1997.

[4] A. V. Nandedkar and P. K. Biswas, "A fuzzy min-max neural network classifier with compensatory neuron architecture," in Proc. 17th ICPR, vol. 4, pp. 553–556, 2004.

[5] A. Quteishat and C. Lim, “A modified fuzzy min-max neural network and its application to fault classification,” in Soft Computing in Industrial Applications. New York, NY, USA: Springer-Verlag, pp. 179–188, 2007.
[6] B. Gabrys and A. Bargiela, “General fuzzy min-max neural network for clustering and classification,” Neural Networks, IEEE Transactions on, vol. 11, no. 3, pp. 769-783, 2000.
[7] H. Zhang, J. Liu, D. Ma, and Z. Wang, “Data-core-based fuzzy min-max neural network for pattern classification,” Neural Networks, IEEE Transactions on, vol. 22, no. 12, pp. 2339-2352, 2011.
[8] L.A. Zadeh, “Fuzzy sets,” Inf. Control, vol. 8, no. 3, pp. 338–353, 1965.
[9] P. K. Simpson, “Fuzzy min-max neural networks. I. Classification,” IEEE Trans. Neural Network, vol. 3, no. 5, pp. 776–786, Sep. 1992.
[10] R. Davtalab, M. H. Dezfoulian, and M. Mansoorizadeh, “Multi-level fuzzy min-max neural network classifier,” Neural Networks and Learning Systems, IEEE Transactions on, vol. 25, no. 3, pp. 470-482, 2014.
[11] Meneganti, Massimo, Francesco S. Saviello, and Roberto Tagliaferri. “Fuzzy neural networks for classification and detection of anomalies.” Neural Networks, IEEE Transactions IEEE Trans. Neural Networks, vol. 9, no. 5, pp. 848–861, 1998.
[12] H. J. Kim, J. Lee, and H. S. Yang, “A weighted FMM neural network and its application to face detection,” in Neural Information Processing, New York, USA: Springer-Verlag, pp. 177–186, 2006.
[13] H. Singh, M. Z. Abdullah, and A. Qutieshat, “Detection and classification of electrical supply voltage quality to electrical motors using the fuzzy-min-max neural network,” in Proc. IEEE IEMDC, pp. 961–965, 2011.
[14] M. Seera, C. P. Lim, D. Ishak, and H. Singh, “Fault detection and diagnosis of induction motors using motor current signature analysis and a hybrid FMM–CART model,” IEEE Trans. Neural Netw. Learn. Syst., vol. 23, no. 1, pp. 97–108, 2012.
[15] P. Rey-del-Castillo and J. Cardeñosa, “Fuzzy min–max neural networks for categorical data: Application to missing data imputation,” Neural Comput. Appl., vol. 21, no. 6, pp. 1349–1362, 2012.
[16] Kaburlasos, Vassilis G., Ioannis N. Athanasiadis, and Pericles A. Mitkas. "Fuzzy lattice reasoning (FLR) classifier and its application for ambient ozone estimation,” International Journal of Approximate Reasoning, pp. 152-188, 2007.
[17] Bose, Bimal K. “Expert system, fuzzy logic, and neural network applications in power electronics and motion control,” Proceedings of the IEEE, pp. 1303-1323, 1994.
[18] A. V. Nandedkar, “An interactive shadow detection and removal tool using granular reflex fuzzy min-max neural network,” in Proc. World Congr. Eng., vol. 2. 2012.
[19] M. Kumar, R. Stoll, and N. Stoll, “A min-max approach to fuzzy clustering, estimation, and identification,” Fuzzy Systems, IEEE Transactions on, vol. 14, no. 2, pp. 248-262, 2006.
[20] S. K. Pal and S. Mitra, “Multilayer perceptron, fuzzy sets, and classification,” IEEE Transactions on Neural Networks, vol. 3, no. 5, pp. 683-697, 1992.
[21] Y.Y. Lin, J.Y. Chang, and C.T. Lin, “Identification and prediction of dynamic systems using an interactively recurrent self-evolving fuzzy neural network,” IEEE Trans. Neural Network. Learn. Syst., vol. 24, no. 2, pp. 310–321, 2013.
[22] A. V. Nandedkar, “An interactive shadow detection and removal tool using granular reflex fuzzy min-max neural network,” in Proc. World Congr. Eng., vol. 2, 2012.
[23] Huang, Mei-Ling, “Usage of case-based reasoning, neural network and adaptive neuro-fuzzy inference system classification techniques in breast cancer dataset classification diagnosis,” Journal of medical systems, pp. 407-414, 2012.
[24] Kıyan T., Yıldırım, T., “Breast Cancer Diagnosis Using Statistical Neural Networks,” In: International XII. Turkish Symposium on Artificial Intelligence and Neural Networks, pp. 754–760, 2003.
[25] Quteishat, Anas, and Chee Peng Lim, “Application of the fuzzy min-max neural networks to medical diagnosis,” Knowledge-Based Intelligent Information and Engineering Systems, Springer Berlin Heidelberg, 2008.
[26] S. S. N. Sivanandam, Principles of soft computing. Wiley India Pvt. Limited, 2007.
[27] A. V. Nandedkar and P. K. Biswas, “A granular reflex fuzzy min-max neural network for classification,” IEEE Trans. Neural Netw., vol. 20, no. 7, pp. 1117–1134, 2009.