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Survey of Fuzzy Min Max Neural Network and Variants

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ABSTRACT: Now a days, Artificial Intelligence has torn the limits of building the new world order. As data has come forward to be an important resource from the last many decades, pattern recognition and pattern classification are coming forward as an emerging fields. Artificial neural networks and Fuzzy logic are widely used in pattern classification. Fuzzy Min-Max(FMM) Neural network is a hybrid model which has been proved to be a most usable models. But along with different capabilities of FMM, it has some limitations. To overcome these limitations, many variants of FMM have been proposed. So this study assists in understanding different existing FMM variants with their current applications. This paper summarizes FMM's use in different sectors and real world issues.

KEYWORDS: FMM, ANN, PCA, Hyperbox

I. INTRODUCTION

Artificial Neural Networks (ANNs) are the mostly used methods for handling pattern classification problems. They can handle non-linear problems. Many ANN structures are available for pattern classification but most of them use offline learning approach for training. As a result, this structure suffers from "catastrophic Forgetting" or "stability-plasticity dilemma".ART i.e. Adaptive Resonance Theory networks uses online training approach and is able to handle stability-plasticity dilemma. But still there are some hyperbox-overlapping issues existed. As a solution to this all, FMMNs are proposed for pattern classification (supervised learning) and pattern clustering (unsupervised learning). The basic fuzzy min-max neural network (FMMN) is capable to perform the supervised classification of data.

Following are some features of FMM networks:

1. Online Learning : Without forgetting existing classes, FMM can learn new classes and improve existing ones
2. Non-linearity: Despite of shapes and sizes, FMM builds non-linear decision boundary to distinguish classes.
3. Overlapping classes: It decreases number of misclassification patterns in overlapping areas.
4. Soft and hard decisions: It supports both hard and soft decisions.

Though FMM can handle the stability-plasticity dilemma, FMM learning methods still suffer from many limitations. To overcome this limitation of FMM, number of FMM variant has been proposed.
But as there is no wide range of research highlighting advantages and disadvantages of this variants is available, FMM variants are blindly choses for various classification issues. In order to contribute to this gap, following paper is written. So in order to reduce this gap, mainly two variants can be given as FMM with contraction process and FMM without contraction process.

This survey focuses on

a. FMM structure and current limitations of FMM
b. FMM variants and their applications
c. Some real life examples

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d. Suggesting some possible improvements.

II. FUZZY MIN-MAX NEURAL NETWORK

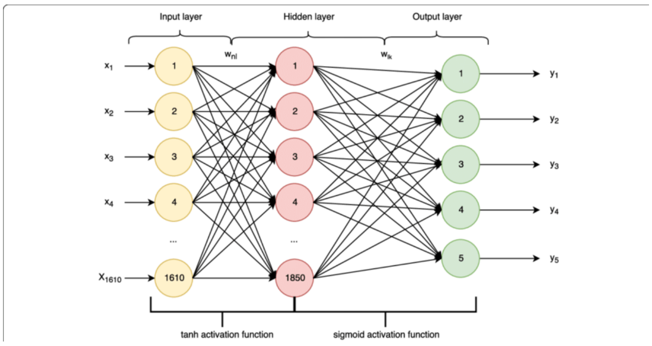

Fig 1. FMM Neural Network Structure

FMM network builds decision boundaries by building hyperboxes in pattern space. Each hyperbox is having a pair of minimum and maximum value points in an n-dimensional space with a member function.

FMM network structure consists of three layers

I. Input layer
II. Hidden layer (Hyperbox)
III. Output layer

Generally, learning of FMM consists of three methods including **expansion process, overlap test, and at the end contraction process.**

Though FMM is effective model in online learning, it still needs many of improvements to be done. The main three methods require most of the improvements. So evolution of this process leads to following variants.

TABLE 1 : FMM Variants with contraption and without contraption

Fuzzy Min Max Neural Network	
Variants with contraction	**Variants without contraction**
GFMM (2000)	Inclusion / Exclusion (2004)
WFMM (2004)	
MFMM (2008)	Adaptive Inclusion / Exclusion (2004)
FMM-GA (2010)	
AFMM	GRFMM
EFMM	FMCN
EFMM II	DCFMN (2011)
K-Nearest (2017)	MLF (2014)

First column procedures keep the original FMM learning stages while second column discards contraction stage.

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FMM variants with contraction

GFMM was proposed by Gabrys and Bargiela as a General FMM and it has extended both classification and clustering. It adapts itself with new type of data. It uses expansion equation, membership function, and network structure for this adaption. GFMM is able to deal with supervised as well as unsupervised learning but still it is affected in overlap test and contraction rules. [9]

Next to this, Kim and Yang developed a weighted FMM network (WFMM).[5] Purpose of adding weight factor is to reflect the frequency factor of feature values. So this model effectively can prevent undesirable performance degradation caused by noisy patterns. But this model also has limitations in expansion, overlap test, and contraction procedures of the original model.

Quteishat and Lim proposed a modified version i.e. MFMM that enhances performance of FMM required the situation when size of expansion parameter is large.[10]

For rule extraction and pattern classification, hybrid model for FMM and Generic algorithm was given by same authors. First stage was for reducing FMM complexity and second one was for decreasing number of features in extracted rules. Adaptive Fuzzy (AFMM) was given by Liu et al. which was based on the principal component analysis (PCA) and adaptive GA for improvement in FMM. This model resulted in maintaining simple shape of original FMM network along with reducing its complexity.

After this, Mohammed and Lim designed an Enhanced FMM (EFMM) model for overcoming number of limitations in original FMM. In his model, expansion procedure is updated using novel expansion rule which leads to reducing overlap areas between hyperboxes. New overlap test for covering all cases and finally, new contraction procedure to eliminate all overlapped cases. EFMM shows efficiency as compared to FMM, GFMM, FMCM and SVM classifiers.[2]

In 2017, FMM network using K-nearest (Kn) hyperbox expansion rule was proposed. It is used to increase accuracy by reducing complexity. It resulted in good classification accuracy with less network complexity.
An extension of EFMM i.e. EFMM-II was further presented. It improved performance of EFMM by two strategies, K- nearest hyperboxes and a pruning strategy.[12]
But over all of this, FMM with contraction undergoes from data distortion problem. It results due to losing part of hyperbox information during contraction method.

Table 2 : FMM with contraction

Limitations					
Model	**Expansion**	**Missing overlap rules**	**Missing contraction rules**	**Data distortion**	**Affected by Noise**
FMM	Y	Y	Y	Y	Y
GFMM	Y	Y	Y	Y	Y
WFMM	Y	Y	Y	Y	Y
MFMM	Y	Y	Y	Y	N
FMM-GA	Y	Y	Y	Y	N
AFMN	Y	Y	Y	Y	N
EFMM	N	N	N	Y	Y
EFMM II	N	N	N	Y	Y
K-Nearest	Y	Y	Y	Y	Y

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FMM variants without contraction

It focuses on discarding contraction method from learning stage. It is done to improve classifier accuracy by avoiding data distortion.
Inclusion and exclusion are two types of hyperboxes proposed by Bargiela et al. It was to overcome problem of contraction procedure in FMM. An issue comes when the size of exclusion hyperbox is relatively large compared with inclusion hyperboxes.

To overcome this weakness, another improved model i.e. adaptive exclusion inclusion was proposed in the same year. A new model called FMCN with compensatory neurons was given by Nandedkar and Biswas to enhance classification accuracy in overlap region. Result shows FMCN performed better than FMM and GFMN. Its weakness is complexity.[13]. IN same year, General Reflex FMM (GRFMM) was proposed by same researchers to handle overlap problem. It is capable of classifying and clustering in just a single pass.

Data core FMM (DCFMM) updates FMM structure by using two neurons. First classifying and second overlapping neurons. DCFMM outperforms FMM, GFMM, and FMCN with decreased computation time.
Multilevel FMM (MLF) was given by Dvtalab et al. It was consisting of two types of subnets to improve classification accuracy in the overlap regions. It shows High performance in training accuracy with low sensitivity w.r.t. expansion parameter.[6].

Table 3 : FMM without contraction

<table>
<tr><th colspan="5">Limitations</th></tr>
<tr><th>Model</th><th>Expansion</th><th>Missing overlap rules</th><th>Affected by Noise</th><th>Complexity</th></tr>
<tr><td>Inclusion/Exclusion</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td></tr>
<tr><td>Adaptive Inclusion/Exclusion</td><td>Y</td><td>Y</td><td>Y</td><td><table>
<tr><th>Model</th><th>Application</th></tr>
<tr><td>FMM</td><td>Handwritten Chinese character recognition</td></tr>
<tr><td>FMM</td><td>Printed English character recognition</td></tr>
<tr><td>GFMM</td><td>Leakage Detection in Water Distribution</td></tr>
<tr><td>FMM-GA</td><td>Power generation Plant Cooling system</td></tr>
<tr><td>MFMM</td><td>Power generation Plant Cooling system</td></tr>
<tr><td>FMM-CART</td><td>offline and online FDD Induction Motors</td></tr>
<tr><td>DCFMN</td><td>Leakage Detection in Oil Pipeline</td></tr>
</table>Y</td></tr>
<tr><td>GRFMM</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td></tr>
<tr><td>FMCN</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td></tr>
<tr><td>DCFMN</td><td>Y</td><td>Y</td><td>N</td><td>Y</td></tr>
<tr><td>MLF</td><td>Y</td><td>Y</td><td>N</td><td>Y</td></tr>
</table>

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III. APPILICATIONS OF VARIOUS VARIENTS

TABLE 4: SOME OF THE APPLICATIONS OF VARIOUS VARIANTS

SVM and FMM	Vehicle Suspension System
WFMM	Face Detection
RFMM	Object Recognition

Attack Intension recognition

Sensitive information can be exposed to risks while communicating over computer networks and to avoid that, FMM neural network can be used as attack intension recognizer. Here, we discussed similarity approach for Attack Intention Recognition using FMM Neural Network.

There are two intentions: intentions.

1. General intentions - recognized by investigating violations against the security metrics of confidentiality, integrity, availability, and authenticity.
2. Specific intentions - recognized by investigating the network attacks used to achieve a violation.

Through this, we get an idea about how fuzzy min max approach is useful in attack intention recognition and how it will provides efficient solution.
At the end, FMM is used for investigating attack.

Intrusion Detection System
In the era of Internet, all the data is travelling through network. So the loopholes in the network may lead to extreme privacy concerns.
So intrusion detection system is proposed which is based on the FMM-GA. This system is tested using KDD CUP dataset and classification accuracy, classification errors are taken as the performance parameter.

Human Action Recognition
Using a hybrid neural network, human action recognition is presented. The method consists of three stages consisting of pre-processing, feature extraction, and pattern classification. CNN is referred for feature extraction. A weighted fuzzy min-max (WFMM) neural network is used for the pattern classification stage. Two kinds of relevance factors between features and pattern classes are defined to analyse the salient features.

IV. CONCLUSION AND FUTURE WORK

FMM has number of shortcomings though it has number of silent features. Number of variant have been proposed to overcome this. Along with a large variety in variants and their specific applications, determining the suitable model for further improvement in this domain become a difficult job. So this survey will help new researchers for selecting appropriate model by having all variants at a single glance together here. So in order to have knowledge of all variants along with their drawbacks and uses, we summarized here different models that are blindly ignored by many researchers. To deliver detailed knowledge of variants to end reader, models are classified as FMM with contraction and FMM without contraction. FMM with contraction suffers from distortion of data resulting in less accurate decisions. Variants without contraction avoid data distortion but overlap test limitations and expansion process limitations still exists. Hence all FMM variants inherit at least one limitation from original FMM. In future,

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number of improvements to this FMM models are possible. One can be to generate an adaptive hyperbox expansion process. New pruning strategy can also be used to reduce model complexity.

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