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AC88008Neuro-Fuzzy Inference System with Meta-Cognitive Learning Algorithm Using Pseudosamples for Classification Problem

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ABSTRACT— *Neuro-Fuzzy Inference System with meta-cognitive learning employs self-regulated human learning mechanism through which its able to adapt self-regulated/self-monitored mechanism in order to decide when, how and what to learn by using respective learning strategies. The proposed system has two components cognitive component and meta-cognitive component. The cognitive component is controlled by meta-cognitive component. The learning is accomplished by using monitory and control signals. The existing McFIS system do not use the past knowledge in the learning process, the proposed McFIS network by making use of knowledge measures which helps to exploits the knowledge acquired by the samples. By incorporating knowledge measure in the learning process the network is able to use the knowledge gained from the past training samples in further learning.*

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I. THE EXISTING META-COGNITIVE NEURO-FUZZY INFERENCE SYSTEM

A lot of work aiming at integrating commonsense and computational intelligence has been done in neural network community, one such work is presented by Naren and Nelsons model on meta-cognitive learning [1]. Nelson and Narens model is simple and easy to understand and use, as Nelson and Naren model, Meta-Cognitive learning in Neuro-Fuzzy Inference system (McFIS) [2] also have two components cognitive and meta-cognitive component. The TSK type 0 system, is the cognitive component, and self-regulatory learning algorithm is the meta-cognitive component. The data stream flow from cognitive component to meta-cognitive component and is called as monitory signals, data stream flow from meta- cognitive component to cognitive component is called as control signals. The self-regulatory learning mechanism monitors the knowledge in the network and controls the learning in the network by deciding on one of the learning mechanism i.e what, when and how to learn. These three learning strategies are as follows:

Delete sample: The sample is deleted because the information present in the sample is already present in the system.
Learning from Sample : If the sample is novel than its used for learning by adding new rule.
Reserve Sample: Some samples may be reserved to be used at later stage for learning.

Therefore by using the above learning mechanism McFIS is able to control *what, when and how to learn* components of meta-cognition using the delete strategy, learning strategy and reserve strategy.

The main issues McFIS addresses are [2]: i) Incorporating human learning mechanism in machine learning for effective learning and better performance. ii) Using class specific criterion for addressing classification problem. iii) Hinge loss error function is used for estimating posterior probability. iv) Gaussian rule is exploited completely.

Though McFIS provides better and efficient performance as compared to other classifiers, there still exist issues in McFIS and they are:

Its computationally intense due to the use of EKF for parameter update.
Not able to use the knowledge acquired earlier for future learning.

The use of extended kalman filter, although guarantees optimal state estimation, its computationally expensive especially for datasets with large number of feature or large rule base. Recently, a fast learning algorithm has been proposed which computes the optimal output weights with least computational effort by finding analytical minima of total error of the network, referred to as Projection Based Learning (PBL) algorithm . By using PBL in McFIS referred as PBL-McFIS [3], it estimates the optimal weight by minimizing the total error (energy) in the network. Thus by using projection-based learning it addresses the issue of McFIS being computationally intense, except the use of past knowledge in further learning.

Similarly PBL algorithm has been employed in Meta-cognitive Radial Basis Function Network referred as PBL-McRBFN[4], in order to make the network less computationally expensive as McRBFN also uses Extended Kalman Filter for parameter upadation. Furhtermore a new enhanced sequential projection based learning algorithm is proposed which not only reduces the computation cost also helps the network to learn more efficiently by using the knowledge gained from past training samples for further learning [5], by using knowledge measures as pseudo-samples.

In the proposed McFIS network by using knowledge measures along with self-regulatory threshold help the network to learn more efficiently by been able to use the knowledge acquired by the samples from the training process.

II. MCRBF USING PBL FOR CLASSIFICATION PROBLEM

Similar to Naren and Nelson model of meta-cognition [1], PBL-Meta-cognitive Radial Basis Function (McRBFN) has two components cognitive component and meta-cognitive component. The data stream flow from cognitive component to meta-cognitive component is called as monitory signals, and the data stream flow from meta- cognitive component to cognitive component is called as control signals. In order to add a new neuron or update the output weights, the cognitive component gets knowledge from the training data stream.

The PBL algorithm here helps to make the system less computationally expensive. It also uses the neurons already present in the cognitive component as knowledge measures. Thereby it helps to exploits the knowledge stored in the network. When a new sample is presented to the cognitive component of McRBFN, The meta-cognitive component calculates the knowledge measures of each sample the knowledge measures in the meta-cognitive component are predicted label of the class, error, and novelty of the sample. For better classification the meta-cognitive component chooses a appropriate learning mechanism i.e the self-regulated rules in the meta-cognitive learning algorithm. The meta-cognitive component also calculates the overlapping between the current training sample and the nearest neurons in the same class or outside the class in order to determine new hidden parameters.

Thus in this way PBL-McRBFN consumes less energy i.e its computationally less expensive, and by using knowledge measures it exploits the past knowledge of the sample, thus it helps the network in learning efficiently and minimizing misclassification. PBL- McRBFN has been compared with the existing classifiers in the literature and it has been observed that it performs better than existing classifiers.

III. PROPOSED MCFIS NETWORK FOR CLASSIFICATION PROBLEM

In this section we are proposing a new learning mechanism in McFIS, through which the network would be able to learn efficiently. In the above discussion we discussed, Meta-cognitive Radial Basis Function Network using PBL algorithm, how PBL algorithm helps the network in becoming computationally less expensive and been able to exploit the knowledge of the sample acquired from past training samples. Here, we are introducing a learning mechanism in McFIS in order to be able to exploit the knowledge present in the samples, by using knowledge measures. When a new sample is presented to the cognitive component of McFIS various knowledge measures are calculated. The knowledge measures are predicted label of the class, error and the novelty of the sample. Using these knowledge measures along with self-regulatory thresholds, two sample-based learning strategies and three neuron-based learning strategies are developed by the meta-cognitive component which are further used for better classification by selecting appropriate learning strategy.

The schematic diagram for the proposed system is as shown in the fig. 1. The cognitive component of McFIS has four layer: input layer, Gaussian layer, normalization layer and output layer. The meta-cognitive component contains knowledge measures and learning strategies. As compared to the existing Meta-cognitive Neuro-fuzzy Inference system the proposed system has two more learning strategies added in order to help the system address how-to-learn aspect of learning, along with that additional knowledge measures we are using for measuring the knowledge in the sample.

The cognitive component has four layer:
Input Layer: The number of nodes *m* in this layer represents the input feature. The output of the input layer is directly transmitted to the Gaussian layer.
Gaussian Layer: It conatins the rule background information of each of the K rule of the McFIS system, and it performs rule inference to compute the overall contribution of the rule to the input features.
Normalization Layer: The number of nodes int this layer is same as Gaussian layer.
Output Layer: The number of nodes in this layer is equal to the number of distinct classes (n).

The Meta-cognitive component: Whenever a new training sample is presented to this component various knowledge measures are calculated based on which the meta-cognitive component of the system is able to control the learning and impose self-regulation . The knowledge measures are predicted label of the class, error, probability, and novelty of the sample as the measures of knowledge in the new training sample. In order to capture knowledge from the samples thresholds are used which acts as self-regulated rules. Based on these calculated knowledge measures and thresholds, the meta-cognitive component is able to select appropriate learning strategies i.e sample-based learning strategies or neuron-based learning strategies to gain knowledge from the current sample.

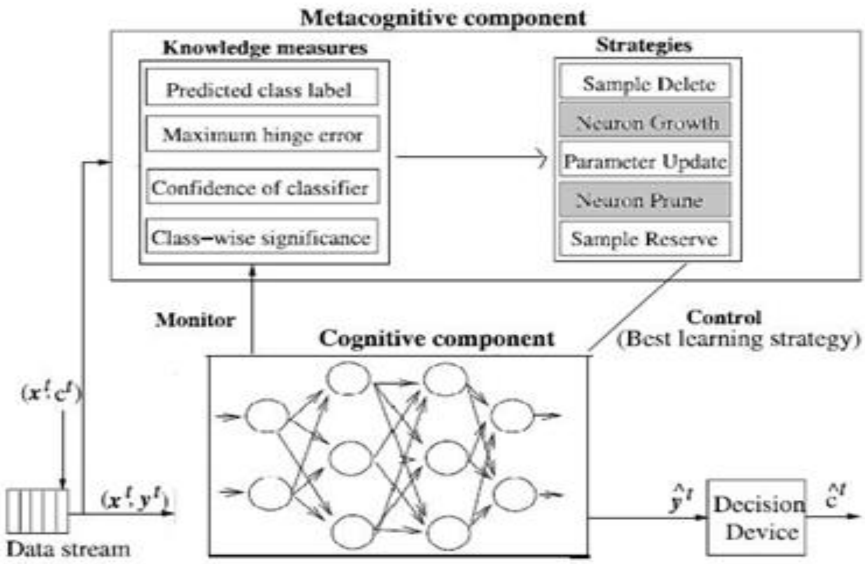

Fig. 1. Schematic diagram of metacognitive learning.

The learning strategies*:* The meta-cognitive component devises various learning strategies using the knowledge measures and the self-regulated thresholds that address the basic principles of self-regulated learning (i.e what, when and how to learn). The learning process in cognitive part is monitored and supervised by the meta-cognitive component with the help of following five learning strategies

Sample Delete **:** When a sample donot have any significant information and the knowledge contained in the sample already exist in the system than the sample is deleted.

Neuron Growth **:** When a sample is novel its used for learning in the network hence a new neuron is added. Whenever a new neuron is added, its taken care that it donot overlaps with other samples. For every new neuron centre and width is assigned according to the nearest neuron. The performance is significantly influenced based on the output weight initialization using new training samples.In the proposed system, the above-mentioned issues can be resolved as follows.

Using the knowledge of past trained samples stored in the network the new neuron output weights will be estimated.
On the basis of new training sample distances to existing samples of same and other class nearest neurons the new neuron center and width parameters will be initialized.

Parameter Update: Whenever a new sample is added the parameters of the cognitive components are updated.
Neuron Pruning: If a particular neuron is not been used for a N no. of samples than that neuron is removed/pruned from the network.
Sample Reserve: If the new training sample donot have significant information but has some information than that sample can be reserved to be learnt later.

In this way the McFIS network addresses the “ what to learn” by using sample delete strategy, by deleting unimportant samples, with the help of neuron growth strategy, parameter update strategy and neuron pruning strategy we will be able to address the “ how to learn” aspect, and by self-adaptive thresholds along with sample reserve strategy addresses the “ when to learn” aspect.

Thus from the above discussion it can be concluded that the learning in McFIS can be improvised by adding new learning strategies, and by using knowledge measures as pseudo-samples of the sample in order to exploit the information stored in the sample, therefore reducing misclassification.

IV. IMPLEMENTATION AND RESULTS

In this section, we present the results of the existing system and proposed system using data sets from the UCI machine learning repository.
Data sets: Iris, Glass Identification, Abolone, Liver and Letter Recognition.
Data set description: *Iris* data set has four features and three classes it’ s a multi-category balanced dataset having equal number of samples per class.
Glass Identification dataset has nine features and six number of classes it’ s a multi-variant unbalanced data set with less number of features and with sample missing values.
Abolone data set has eight features and three classes it’ s a multivariate data set for predicting the age of abalone.
Liver data set is considered as binary problem dataset with smaller number of features, it has six features and two no. of classes.
Letter Recognition dataset has sixteen no. of features and twenty-six no. of classes. It’ s a multi-category problem with more number of samples and classes.
Table I gives the specification of all the employed data sets.

Table II

Performance results for various multi-category datasets

Data sets	Algorithm	CPU (secs)	Rules		Testing				Accuracy
					no		ng		
			MEAN	SD	MEAN	SD	MEAN	SD	
GI	McFIS Optimized McFIS	0.0038 0.025	20.88 20.62	40.70 39.10	15.53 11.43	28.46 27.73	26.18 24.21	50.45 49.32	96.72% 97.66%
IRIS	McFIS Optimized McFIS	0.003 0.020	3.46 3.12	1.97 1.43	2.89 2.10	1.89 1.54	4.03 3.91	1.88 1.73	98.00% 99.00%
LIVER	McFIS Optimized McFIS	0.003 0.019	42.80 41.21	35.15 34.90	41.07 39.50	34.25 34.00	44.49 43.99	35.93 34.19	80.28% 89.13%
LETTER	McFIS Optimized McFIS	0.003 0.107	5.91 5.51	2.93 2.12	5.912 5.211	2.942 1.911	5.911 4.991	2.922 2.450	16.52% 57.18%
ABOLONE	McFIS Optimized McFIS	0.002 0.034	1.63 1.63	3.62 3.61	1.63 1.61	3.61 3.61	1.64 1.63	3.63 3.62	86.63% 91.59%

This experiment is conducted for all these data sets in MATLAB R2013b environment in a core i5 processor with 4GB RAM in windows environment.

PERFORMANCE MEASURES

The performance of the McFIS and proposed system is observed using the measures: overall accuracy (no) and geometric mean accuracy (ng) for the input data sets.

Table II represents the number of rules and overall accuracy for the existing system and the proposed system along with mean and standard deviation values.

From Table II it can be seen that the proposed system provides better results as compared to the existing McFIS. Referring Table II for performance comparison the proposed McFIS gives approximately 9% better accuracy than the existing McFIS system for the binary problem Liver data set, and also for data set with large samples having large class labels like Letter recognition data set there is a significant amount of improvement in the accuracy, letter recognition data set is having large number of samples and class labels it' s a multi-category problem and the results that we get for the proposed system is approximately 10-14% better accuracy than the McFIS system.

For balanced data set like Iris we are getting around 1-2% better accuracy than McFIS same with unbalanced dataset like Glass identification with sample imbalance we are getting 1% better accuracy for the proposed McFIS with less number of rules.

From the above discussion it can be concluded that we are able to achieve better accuracy with less number of rules for the proposed algorithm as compared to the existing algorithm.

Table I

Specification of the datasets

DATA SETS	No. of features	No. of Classes	No. of samples
IRIS	4	3	150
GI	9	6	214
Abolone	8	3	4177
Liver	6	2	345
Letter	16	26	2500

V. CONCLUSION

From the above discussion it can be concluded that by incorporating knowledge measures in the learning process of the McFIS network, it enables the network to exploit the knowledge acquired from past training samples and would help it use for further learning process. Thus it helps to achieve optimized output as compared to the existing system with improved accuracy and less number of rules therefore reducing the misclassification rate in the network.

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