IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 6, Dec-Jan, 2014
ISSN: 2320 - 8791
www.ijreat.org

Composition Of Sequential Cognitive Learning And Fuzzy Means Using Classification Techniques

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ABSTRACT

One of the most important aspects of Neural Network is the learning process. The learning process of a Neural Network can be viewed as reshaping a sheet of metal, which represents the output (range) of the function being mapped. The complexity in this system are long iterative nature, long convergence times, existing neuron centers leads to misclassification, Time consumption, Noise data tenser corruption and nonlocal communication in the network being trained and are computationally expensive. This paper combines problem classifier solution which includes topic sequential cognitive learning, fuzzy means to identify a new technique for tree decision and rule based methods, fisher's linear discriminants, and k-nearest-neighbour (or) k-means technique . This paper will assure 80 % accuracy and efficiency. In near future it will be implemented in any customized domain.

Keywords : Neural network, Fuzzy means, Sequential cognitive learning, K-Means Technique, Customized domain

1.INTRODUCTION

An Neural Network (NN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron the inputs are weighted what means that every input value is multiplied with individual weight. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron the sum of previously weighted inputs and bias is passing trough activation function that is also called transfer function.

In order to fully harvest the benefits of mathematical complexity that can be achieved through interconnection of individual artificial neurons and not just making system complex and unmanageable we usually do not interconnect these artificial neurons randomly. In the past, researchers have come up with several "standardized" topographies of artificial neural networks. These predefined topographies can help us with easier, faster and more efficient problem solving. Different types of artificial neural network topographies are suited for solving different types of problems. After determining the type of given problem we need to decide for topology of artificial neural network we are going to use and then fine-tune it. We need to fine-tune the topology itself and its parameters.

2.LITERATURE SURVEY

It gives the description of literature reviewed from various research papers published in international and national journal, proceeding of various conferences and books.

[A] **Giduthuri Sateesh Babu, Sundaram Suresh**,“ Sequential Projection-Based Metacognitive Learning in a Radial Basis Function Network for Classification Problems”.

We present a sequential projection based metacognitive learning algorithm in a radial basis function network (PBL-McRBFN) for classification problems. The algorithm is inspired by human metacognitive learning principles and has two components: a cognitive component and a metacognitive component. The cognitive component is a single-hidden-layer radial basis function network with evolving architecture. The metacognitive component controls the learning process in the cognitive component by choosing the best learning strategy for the current sample and adapts the learning strategies by implementing self-regulation. In addition, sample overlapping conditions and past knowledge of the samples in the form of pseudo samples are used for proper initialization of new hidden neurons to minimize the misclassification. The parameter update strategy uses projection-based direct minimization of hinge loss error. The interaction of the cognitive component and the metacognitive component addresses the what-to-learn, when-tolerant, and how-to-learn human learning principles efficiently. The performance of the PBL-McRBFN is evaluated using a set of benchmark classification problems from the University of California Irvine machine learning repository. The statistical performance evaluation on these problems proves the superior performance of the PBL-McRBFN classifier over results reported in the literature. Also, we evaluate the performance of the proposed algorithm on a practical Alzheimer’s disease detection problem. The performance results on open access series of imaging studies and Alzheimer’s disease neuroimaging initiative datasets, which are obtained from different demographic regions, clearly show that PBL-McRBFN can handle a problem with change in distribution.

[B] Alex Alexandridis , Eva Chondrodima, and Haralambos Sarimveis (Feb 2013)“Radial Basis Function Network Training Using a Nonsymmetric Partition of the Input Space and Particle Swarm Optimization”.

This paper presents a novel algorithm for training radial basis function (RBF) networks, in order to produce models with increased accuracy and parsimony. The proposed methodology is based on a nonsymmetric variant of the fuzzy means (FM) algorithm, which has the ability to determine the number and locations of the hidden-node RBF centers, whereas the synaptic weights are calculated using linear regression. Taking advantage of the short computational times required by the FM algorithm, we wrap a particle swarm optimization (PSO) based engine around it, designed to optimize the fuzzy partition. The result is an integrated framework for fully determining all the parameters of an RBF network. The proposed approach is evaluated through its application on 12 real-world and synthetic benchmark datasets and is also compared with other neural network training techniques. The results show that the RBF network models produced by the PSO-based nonsymmetric FM algorithm outperform the models produced by the other techniques, exhibiting higher prediction accuracies in shorter computational times, accompanied by simpler network 1structures.

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3. PROBLEM IDENTIFICATION

The feature extraction of image in brain tumor identification researches based an PBL-McRBFN classification results with the following problems. Inability to identify the RBF center. Which result with infinite search in target node (Looping search).more over non-predictable and non-computable in hidden layers. More noise data and misclassification due to computational intensive EKF for parameter updation. Finally non-communicational in the network lead to computably expensive system.

4. IMPLEMENTATION

4.1 .K-Means Algorithm

The idea is that it is most likely to be near to observations from its own proper population. So we look at the five (say) nearest observations from all previously recorded Irises, and classify the observation according to the most frequent class among its neighbours.

4.2 .Fuzzy Means

A fuzzy means is a concept of which the meaningful content, value, or boundaries of application can vary considerably according to context or conditions, instead of being fixed once and for all. This generally means the concept is *vague*, lacking a fixed, precise meaning, without however being meaningless altogether.

Combining these two algorithms we will achieve more than 76% in brain tumor feature extraction problems.

5.PROPOSED ALGORITHM

5.1 .K-Means Algorithm

The idea is that it is most likely to be near to observations from its own proper population. So we look at the five (say) nearest observations from all previously recorded Irises, and classify the observation according to the most frequent class among its neighbours.

5.2 . K-Means Clustering Algorithm includes The Following Steps.

STEP 1: Set k: Choose a number of desired clusters, k.
STEP 2: Initialization: Choose k starting points to be used as initial estimates of the cluster centroids. These are the initial starting values.
STEP 3:Classification: Examine each point in the data set and assign it to the cluster Whose centroid is nearest to it.
STEP 4:Centroid Calculation: When each point is assigned to a cluster, recalculate the new k centroids.
STEP 5:Convergence condition: Repeat steps 3 and 4 until no point changes its cluster assignment, or until a maximum number of passes through the data set is performed.

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5.3 K-MEANS ALGORITHM STEPS AS FOLLOWS

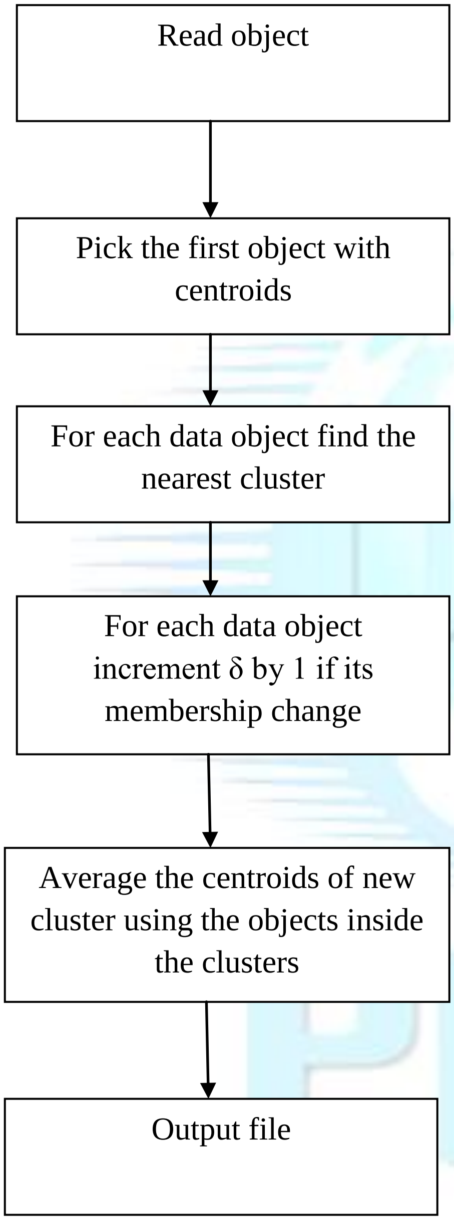

Fig 5.1 Steps for K-Means Algorithm

6. RESULTS AND DISCUSSION

S.No	Image Name	Image Size (in MB)
1	Input image Before Segmentation Process.	192
2	Output Image After Segmentation Process.	16

Table 6.1 Detail of input and output image size in MB

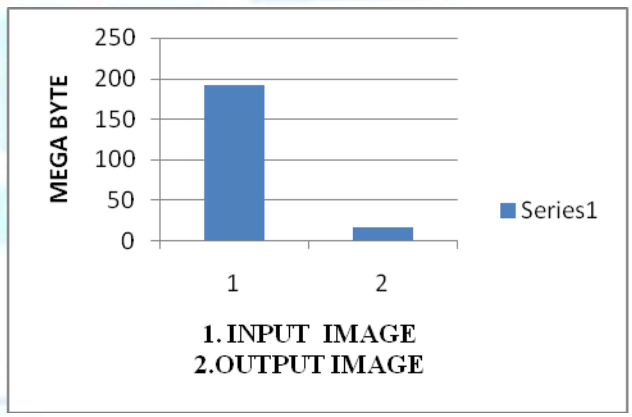

Fig 6.1 Detail of input and output image size in MB

S.no	Classifier	Space Accuracy (%)
1.	PBL-McRBFN	76
2.	K-MEAN	88

Table 6.2 Detail of classifier and space Accuracy with percentage.

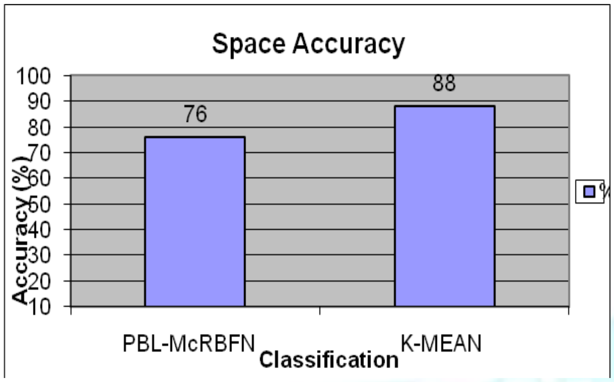

Fig 6.2 Detail of classifier and space Accuracy with percentage.

7. CONCLUSION

In this paper, the implementation of K-Means algorithm using neural network was identified with respect to the space reduction and management. The achieved results are as follows, space accuracy of 88 % and reduction space size of 16 MB were improved respectively. In future this paper will be extended to the implementation of enhanced version towards this algorithm in order to overcome the existing system. Moreover the implementation of fuzzy means will play a vital role in this identification of brain tumor feature extraction.

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