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CLUSTERING OF RANDOM COGNITIVE LEARNING AND FUZZY MEANS USING CLASSIFICATION TECHNIQUES

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ABSTRACT

Clustering is the task of grouping a set of objects in such a way that objects in the same group called as cluster are more similar in some sense or another to each other than to those in other groups clusters. Including machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics. 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 clustering means to identify new technique for Simple random, Stratified random, Purposive, Quota, Snowball, Volunteer, accidental, convenience and Cluster to the above algorithm which uses random technique for the implementation of learning process. This paper will assure 76 % and above to produce the accuracy and efficiency in brain tumor . In near future it will be implemented in any customized domain.

Index Terms : Clustering , Fuzzy cluster means, Sequential cognitive learning, Cluster, simple random, Stratified random, Purposive, and Quota Technique, Customized domain.

I.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.

II.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] **Qi Mao, Ivor Wai-Hung Tsang** (Feb 2013)”Efficient Multitemplate Learning for Structured Prediction”

Conditional random fields (CRF) and structural support vector machines (structural SVM) are two state-of-theart methods for structured prediction that captures the interdependencies among output variables. The success of these methods is attributed to the fact that their discriminative models are able to account for overlapping features on all input observations. These features are usually generated by applying a given set of templates on labeled data, but improper templates may lead to degraded performance. To alleviate this issue, in this paper we propose a novel multiple template learning paradigm to learn structured prediction and the importance of each template simultaneously, so that hundreds of arbitrary templates could be added into the learning model without caution. This paradigm can be formulated as a special multiple kernel learning problem with an exponential number of constraints. Then we introduce an efficient cutting-plane algorithm to solve this problem in the primal and present its convergence. We also evaluate the proposed learning paradigm on two widely studied structured prediction tasks, i.e., sequence labeling and dependency parsing.Extensive experimental results show that the proposed method outperforms CRFs and structural SVMs because of exploiting the importance of each template. Complexity analysis and empirical results also show that the proposed method is more efficient than Online multikernel learning on very sparse and high-dimensional data. We further extend this paradigm for structured prediction using generalized *p*-block norm regularization with *p* > 1, and experiments show competitive performances when *p* □ [1, 2)..

[B] **Yue Deng, Qionghai Dai, Risheng Liu, Zengke Zhang** (march 2013) ”Low-Rank Structure Learning via Nonconvex Heuristic Recovery”

We propose a nonconvex framework to learn the essential low-rank structure from corrupted data. Different from traditional approaches, which directly utilizes convex norms to measure the sparseness, our method introduces more reasonable nonconvex measurements to enhance the sparsity in both the intrinsic low-rank structure and the sparse corruptions. We will, respectively, introduce how to combine the widely used _ *p* norm (0 < *p* < 1) and log-sum term into the framework of low-rank structure learning. Although the proposed optimization is no longer convex, it still can be effectively solved by a majorization–minimization (MM)-type algorithm, with which the nonconvex objective function is iteratively replaced by its convex surrogate and the nonconvex problem finally falls into the general framework of reweighed approaches. We prove that the MM-type algorithm can converge to a stationary point after successive iterations. The proposed model is applied to solve two typical problems: robust principal component analysis and low-rank representation. Experimental results on low-rank structure learning demonstrate that our nonconvex heuristic methods, especially the log-sum heuristic recovery algorithm, generally perform much better than the convex-norm-based method (0 < *p* < 1) for both data with higher rank and with denser corruptions.

III.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

IV.IMPLEMENTATION

A)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.

B)Fuzzy Cluster Means

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. The FCM algorithm attempts to partition a finite collection of elements X={x_1, x_2, ... , x_n} into a collection of c fuzzy clusters with respect to some given criterion.

Minimization of the following objective function

$$J_M = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \|x_i - c_j\|^2 \quad \text{----------- (1)}$$

Where i) m is any real no greater than 1.

ii) u_{ii} degree of membership of x_i in the cluster j,

ii) x_i is the ith of d-dimensional data,

iii)c_j is the d-dimensional center of the cluster

iv) ||*|| is any norm expressing the similarity between any measured data and center.

fuzzy partitioning is carried out through an iterative optimization of the objective function. The update of membership u_{ij} and cluster center c_j by:

$$c_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} . x_i}{\sum_{i=1}^{n} u_{ij}^{m}}$$

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

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V.PROPOSED ALGORITHM

A) *Fuzzy Cluster Means*

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B) *Fuzzy Cluster Means Algorithm includes The Following Steps*.

STEP 1: initialize $U=[u_{ij}]$ matrix , $U^{(0)}$

STEP 2: At k-Step: Calculate the center Vectors $c^{(k)}=[c_j]$ with $u^{(k)}$ and distance

$$C_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} . x_i}{\sum_{i=1}^{n} u_{ij}^{m}}$$

STEP 3: Update $U^{(k)}, U^{(k+1)}$

STEP 4: If $\| U^{(u+1)} - U^{(k)} \| < €$ then stop;

Otherwise return to step 2.

C) *FUZZY CLUSTER MEANS ALGORITHM STEPS AS FOLLOWS*

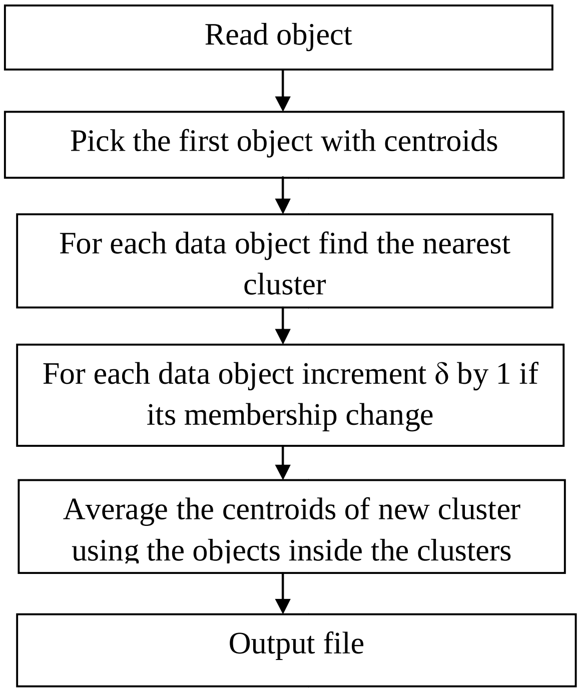

Fig 5.1 Steps for Fuzzy Cluster Means Algorithm.

VI.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

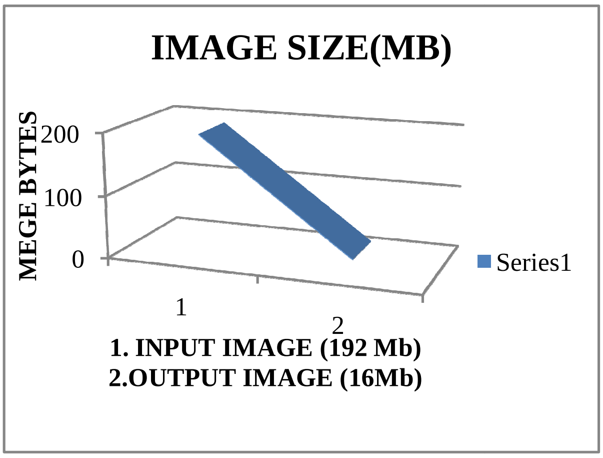

Fig 6.1 Detail of input and output image size in MB

S.no	Classifier	Space Accuracy (%)
1.	PBL-McRBFN	76
2.	FUZZY CLUSTER MEANS	82

Table 6.2 Detail of classifier and Accuracy with percentage.

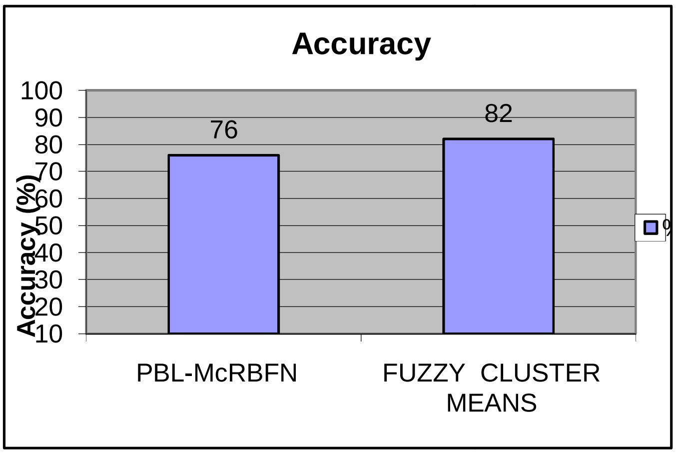

Fig 6.2 Detail of classifier and Accuracy with percentage.

VII CONCLUSION

In this paper, the implementation of fuzzy cluster means algorithm using neural network was identified with respect to the space reduction and management. The achieved results are as follows, space accuracy of 82 % and reduction space size of 16 MB were improved respectively. In future this paper will be implemented towards any medical resolution for brain tumor system. Moreover the implementation of fuzzy cluster means will play a vital role in this identification of brain tumor feature extraction.

REFERENCES

[1] Albayrak, S.—Armasyali, F(2003)" Fuzzy C-Means Clustering on edical Diagnostic System". Proc. Int. XII Turkish Symp. on Artif. Intel. NN.

[2] Alex Alexandridis , Eva Chondrodima, and Haralambos Sarimveis,(2013) "Radial Basis Function Network Training Using a Nonsymmetric Partition of the Input Space and Particle Swarm Optimization" , IEEE Transaction on neural networks and Learning system Vol:24,Pg.219-230.

[3] Babu G., Murthy M., (1993) " A near-optimal initial seed value selection in K-means algorithm using a genetic algorithm", Pattern Recognition, Vol.14, No.10.

[4] BabuS.G,. Savitha R, and S. Suresh, "A projection based learning in meta-cognitive radial basis function network for classification problems," in Proc. Int. Joint Conf. Neural Network., 2012, pp. 2907–2914.

[5] BabuS.G, Suresh ,S, and B. S. Mahanand, "Alzheimer's disease detection using a projection based learning meta-cognitive RBF network," in Proc. Int. Joint Conf. Neural Network., 2012, pp. 408–415.

[6] Bezdek, J. C(1981)"Pattern Recognition with Fuzzy Objective Function Algorithms",Kluwer Academic Publishers, Norwell, MA, USA.

[7] Giduthuri Sateesh Babu, Sundaram Suresh,(Feb 2013) " Sequential Projection-Based Metacognitive Learning in a Radial Basis Function Network for Classification Problems", IEEE Transaction on neural networks and Learning system Vol:24,Pg.194-206.

[8] James c. Bezdek , Robert Ehrlich,(1984)" FCM: The Fuzzy C-Means Clustering Algorithm" International Journal Computer and Geosciences Vol:10,No:2-3,pp:191-203.

[9] Kaufman L. and Rouseeuw P., (1990)"Finding Groups in Data: An Introduction to cluster analysis." Wiley & Sons.

[10] Kloppel.S, C. Stonnington M., C. Chu, B. Draganski, R. I. Scahill, J. D. Rohrer, N. C.Fox, C. R. Jack, Jr., J. Ashburner, and R. S. J. Frackowiak,(2008) "Automatic classification of MR scans in Alzheimer's disease," Brain, vol. 131, no. 3, pp. 681–689.

[11] Krinidis, S.—Chatzis, V.(2010),"A Robust Fuzzy Local Information C-Means Clustering Algorithm". IEEE Trans. on Image Processing, Vol. 19, No. 5, pp. 1328–1337.

[12] Krishna.K,M. Murty,(1999)"Genetic K-means algorithm." IEEE Trans. Syst.,Man, Cybern. vol. 29, no. 3, pp. 433 – 439.

[13] Mahanand.S.B, Suresh .S, Sundararajan .N, and M. A. Kumar,(2012) "Identification of brain regions responsible for Alzheimer's disease using a self-adaptive resource allocation network," Neural Netw., vol. 32, pp.313–322.

[14] Marcus.S.D, Wang .T. H, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, Open access series of imaging studies (OASIS): Crosssectional MRI data in young, middle aged, nondemented, and demented older adults," J. Cognit. Neurosci., vol. 19, no. 9, pp. 1498–507.

[15] Qi Mao, Ivor Wai-Hung Tsang, (Feb 2013)"Efficient Multitemplate Learning for Structured Prediction" IEEE Transaction on neural networks and Learning system Vol:24,Pg.248-261.

[16] Rajasekaran. S, VijayaLakshmi Pai.G.A,(2007)"neural networks ,fuzzy logic, Genetic Algorithm Synthesis and Application", PHI Private Limited.

[17] Rui Xu, Donald Wunsch II, (2005) "Survey of Clustering Algorithms." IEEE Transactions on Neural Networks, Vol.16, No.3.

[18] Tapas Kanungo, David M Mount,(2002),"An Efficient K-means Clustering Algorithm: Analysis and Implementation." Pattern Analysis and Machine Intelligence, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 7.

[19] Yang.W, H. Xia, B. Xia, L. M. Lui, and X. Huang, "ICA-based feature extraction and automatic classification of AD-related MRI data," in Proc.6th Int. Conf. Natural Computer, vol. 3. Aug. 010, pp. 1261–1265.

[20] Yue Deng, Qionghai Dai, Risheng Liu, Zengke Zhang, (March 2013) "Low-Rank Structure Learning via Nonconvex Heuristic Recovery", IEEE Transaction on neural networks and Learning system, Vol:24, Pg.383-396.

[21] Zhang, D. Q.—Chen, S. C.(2004)"A Novel Kernelized Fuzzy C-Means Algorithm With Application in Medical Image Segmentation", Artif. Intel. Med, Vol. 32, pp. 37–50.

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