Local Independent Projection Based Classification Using Fuzzy Clustering

R.Sathya, Mrs.M.Saraswathi.

P.G Scholar,
Dept. of Electronics and communication Engineering
Sri Muthukumaran Institute Of Technology
Chennai,Tamilnadu,India
Sathya.be60@gmail.com
Associate Professor,
Dept. of Electronics and communication Engineering
Sri Muthukumaran Institute Of Technology
Chennai,Tamilnadu,India
saraswathikannang@gmail.com

***ABSTRACT*- Segmentation is a vital role in medical image processing, where clustering technique widely used in medical application particularly for brain tumour detection in magnetic resonance imaging (MRI).We propose a novel automatic tumour segmentation method for MRI images. This method treats tumour segmentation as a classification problem. Additionally, the local independent projection-based classification (LIPC) method is used to classify each voxel into different classes. A novel classification framework is derived by introducing the local independent projection into the classical classification model. we applied adaptive mean shift algorithm to real MRI data and its performance is compared with other clustering methods including K-Means clustering and Fuzzy C-Means clustering. The transformation of an image into its set of features is known as feature extraction. It is a challenging task to extract good feature set for classification. Support vector machine (SVM) is one of the techniques used for the classification purpose .**

1. INTRODUCTION

In Medical diagnosis, through Magnetic Resonance Images Robustness and accuracy of the Prediction algorithms are very important, because the result is crucial for treatment of Patients. There are many popular classification and clustering algorithms used for predicting the diseases from Images. The goal of clustering a medical image is to simplify the representation of an image into a meaningful image and make it easier to analyze. Several Clustering and Classification algorithms are aimed at enhancing the Prediction accuracy of diagnosis Process in

detecting1 abnormalities such as Cancer and white matter lesions from MR Images. Tumor is an uncontrolled growth of tissues in any part of the body.

Image mining facilitates the extraction of hidden information, image data association, or other patterns not clearly accumulated in the images. Image mining is an interdisciplinary effort that provides significant application in the domain of machine learning, image processing, image retrieval, data mining, database, computer vision, and artificial intelligence. Even though there exists growth of several applications and techniques in the individual research domain mentioned above, research in image mining has to

be explored and investigated their existing research problems in image mining, modern growth in image mining, predominantly, image mining frameworks, modern techniques and systems.

Brain tumor segmentation is an important procedure for early tumor diagnosis and radiotherapy planning. The American Brain Tumor Association estimates that about 40,900 people will be diagnosed with a primary brain tumor (rate of 14 percentage of 100,000 people) and 12,900 peoples die due to brain tumor. The segmentation technique helps medical image solutions in higher frequency and it has more impact on medical image processing. The image segmentation process has been used in variety of medical problems from identifying born crush to brain tumors. All MR images are affected by random noise. The noise comes from the stray currents in the detector coil due to the fluctuating magnetic fields arising from random ionic currents in the body, or the thermal fluctuations in the detector coil itself. When the level of noise is significant in an MR image, tissues that are similar in contrast could not be delineated effectively, causing errors in tissue segmentation.
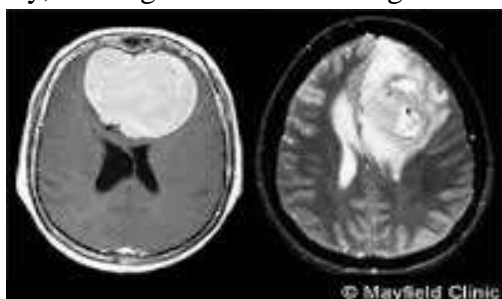

Fig.1 Affected brain

II. SCOPE OF THE OBJECT

MRI Brain image classification and anatomical structure analysis are proposed based on normalization test for classification. LIPC with additionally Spatial Fuzzy clustering for tumor detection and morphological Approach in 2D view. Using a probabilistic geometric model of sought structures and image registration serves . Tumor consuming part is calculated and seed point is fixed automatically then it is compared quantitatively and database images are also used to compare. Image is divided in to 2 parts then seed point is fixed automatically and Volume

calculation produces accurate result . we used a softmax model to learn the relationship between the data distribution and reconstruction error norm. Both synthetic data and public available brain tumor image data are used to compare with databases. The proposed method was compared with other methods by uploading the segmentation results to the online evaluation tool. It has three different types they are as follows.

- ➢ SRM
- ➢ SVM and
- ➢ LAE

III. BLOCK DIAGRAM

Fig.2 shows the project block diagram which has various modules to get accurate affected part. For the pre-processing small changes in the input may cause large changes in the wavelet coefficients. Furthermore aliasing occurs due to down sampling.
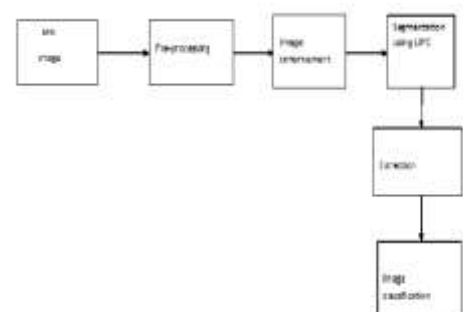

Fig.2 Overview of the project

A. Basic CLAHE Algorithm

This algorithm shows small changes in the input may cause large changes in the wavelet coefficients. Furthermore aliasing occurs due to down sampling. Inverse cancels this aliasing provided if the wavelet and scaling coefficients are not changed (e.g., noise, thresholding). The other disadvantage of DWT is its poor directional selectivity (e.g., inability to distinguish between +45° and −45° spectral features). These problems of Real adaptive median filter can be solved using clear up the image. However, a further problem arises in achieving perfect reconstruction for

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complex wavelet decomposition beyond level 1. To overcome this, Kingsbury proposed histogram, which allows perfect reconstruction while still providing the other advantages of complex wavelets.

Calculate the maximafrom the thresholding uses analytic filters to perform the wavelet analysis. It uses two Real pixel to implement its real and imaginary parts. In order to extend the transform to two-dimensional signals, a filter bank is applied separably in all dimensions. To compute the 2D maximization of images the pair of trees are applied to the rows and then the columns of the image.

GLCM is a matrix that produces six high-pass sub bands as well as two low pass sub bands at each level of decomposition. L represents low pass filters and H represents high pass filters. Each filtering operation is followed by a down sampling by two. Six directional wavelets are obtained by taking sum (Σ) and difference (Δ) of high-pass subbands which have the same pass bands.

As a result wavelets oriented at $\pm15°$, $\pm45°$ ve $\pm75°$ are obtained as

Denoised image is obtained by performing inverse after modifying the wavelet coefficients according to some rules. 4:1 redundancy for 2D images, this redundancy allows both shift invariance and good directional sensitivity.

IV. PRE-PROCESSING

Brain MR images are subjected to be corrupted by noise during the image transmission and image digitization during the process of imaging. Pre-processing is a process to remove these noises from the MRI Brain image by using filter. The extra-cranial tissues such as bone, skin, air, muscles, fat are also removed from the image. It also converts the heterogeneous image into homogeneous image. Any filter will remove the noise in an image but also will corrupt minute details of the image. Also the conventional filters will smooth the image continuously and therefore harden the edges of the image. We adopt anisotropic diffusion filter for the pre-processing of brain MR images since it removes the noise and also preserves the edges. For an image with noise, at the edges, the features get blurred.

In the area of computer vision, by exploiting the concept of visual contexts, one can quickly focus on candidate regions, where objects of interest may be found, and then compute additional features through the descriptor for those regions only. These additional features, while not necessary for global regions, are useful in accurate detection and recognition of smaller objects. Similarly, it may be applied to detect the activated voxels of cortex and additionally the temporal independent component analysis (tICA) may be utilized to extract the underlying independent sources whose number is determined by Bayesian information criterion.
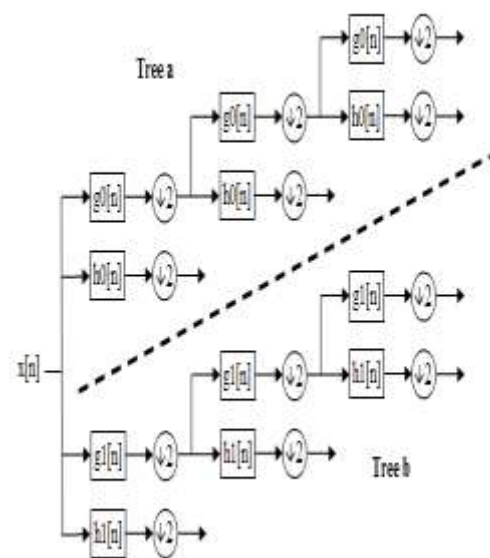

Fig.3 Block diagram of 3-level DTCWT

V. OVER VIEW OF CLUSTERING

Many clustering algorithms have been introduced in the literature. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are fuzzy or crisp (hard). Hard clustering methods are based on classical set theory, and require that an object either does or does not belong to a cluster. Hard clustering means partitioning the data into a specified number of mutually exclusive subsets. *Fuzzy clustering* methods, however, allow the objects to belong to several clusters simultaneously, with different degrees of membership. In many situations, fuzzy clustering is more natural than hard clustering. Objects on

the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership. The discrete nature of the hard partitioning also causes difficulties with algorithms based on analytic functionals, since these functionals are not differentiable.

Fuzzy c-means clustering

In fuzzy clustering, every point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster, may be *in the cluster* to a lesser degree than points in the center of cluster. An overview and comparison of different fuzzy clustering algorithms is available. Most analytical fuzzy clustering algorithms (and also all the algorithms presented in this chapter) are based on optimization of the basic *c*-means objective function, or some modification of it. Hence we start our discussion with presenting the fuzzy *c*means functional. The minimization of the *c*-means functional represents a nonlinear optimization problem that can be solved by using a variety of methods, including iterative minimization, simulated annealing or genetic algorithms. The most popular method is a simple Picard iteration through the first-order conditions for stationary points , known as the fuzzy *c*-means (FCM) algorithm.

OVER VIEW OF CLUSTERING

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VI. SIMULATION RESULTS

Simulation has been performed by using the MATLAB 2013c to detect the tumor . Figure 4 shows output of preprocessing image
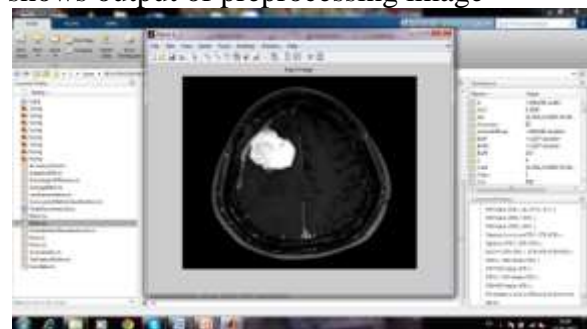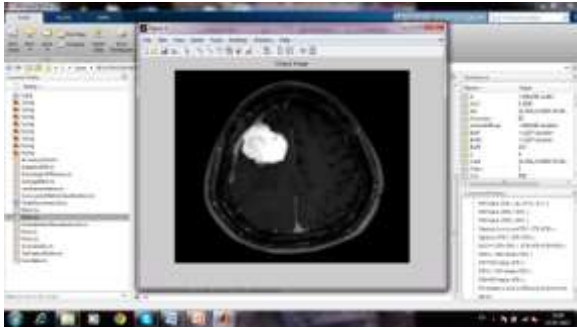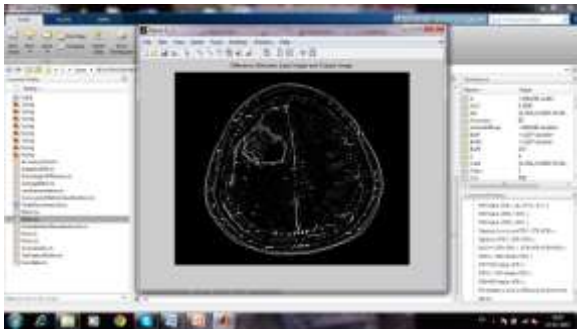

Fig4 : Input image

Fig5: Output Image.

Fig6: Difference between input and output image.
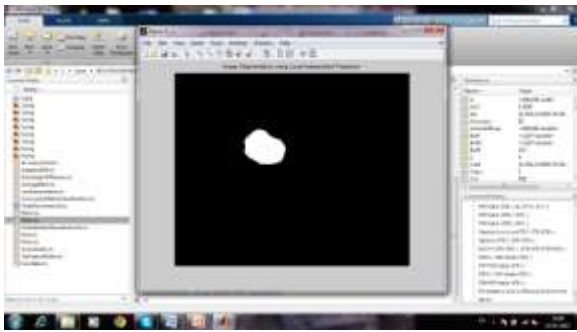

Fig7: Applying LIPC

Fig8: Applying SVM

Fig9: Neural network.

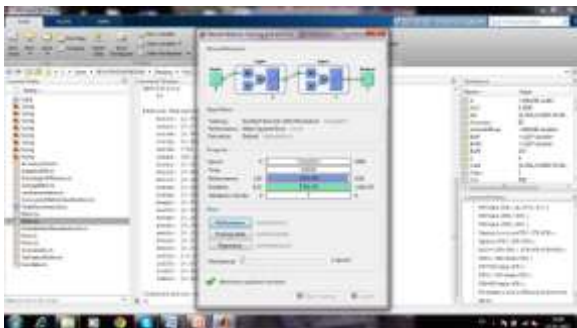## VII.CONCLUSION & FUTURE WORK

The proposed algorithm gives a detecting image based on wavelet transform by applying Dual tree complex wavelet transform on the MRI image. It is a two dimensional wavelet transform is applied to the image . A new method to detecting tumor in 3 dimension view is future work to find full clear vision.

VIII. REFERENCES

[1]   Hassan   Khotanloua,   OlivierColliotb, JamalAtifc, and   IsabelleBlocha (2009), "3D brain tumor segmentation in MRI using fuzzy classification, symmetry analysis and spatially constrained deformable models" , Journal of Fuzzy Sets and Systems 160 ,Vol. 160,pp. 1457–1473.

[2]   James C. Bezdek, Robert Ehrlich and William Full (1984), "FCM: The Fuzzy c-means Clustering Algorithm", Journal of Computers & Geosciences ,Vol. 10, No. 2-3, pp. 191-203.

[3]   Karuna1   M,   Ankita   Joshi (2012),"Automatic Detection and Severity analysis of brain tumors using GUI in matlab". International Journal of Research in Engineering and Technology, Vol. 2, Issue. 10, pp. 586-594.

[4]   Manoj   K   Kowar   and   Sourabh Yadav(2012),"Brain Tumor Detction and Segmentation   Using   Histogram Thresholding", International Journal of Engineering and Advanced Technology (IJEAT), Vol. 1,No. 4,pp. 16-20.

[5]   Meiyan Huang, Wei Yang, Yao Wu, Jun Jiang, Wufan Chen,   Senior

Member, IEEE, and Qianjin Feng (2013), "Brain Tumor Segmentation Based on Local Independent Projection-based Classification ",IEEE Journal of Biomedical Engineering, Vol, 3,No. 7, pp. 1-13.

[6] Mukesh Kumar and Kamal Mehta (2011), "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method", Int. J. Comp. Tech. Appl., Vol 2, pp. 855-859.

[7] Selvakumar J, Lakshmi A and Arivoli T (2012) ,"Brain Tumor Segmentation and Its Area Calculation in Brain MR Images using K-Mean Clustering and Fuzzy C-Mean Algorithm", Proc International Conference On Advances In Engineering, Science And Management (ICAESM) ,Vol.3,No. 2,pp 186-190.

[8] Shantha Kumar P and Ganesh Kumar P (2014), "Performance Analysis of Brain Tumor Diagnosis based on soft computing techniques", American Journal of Applied Sciences, vol. 11, No.2, pp. 329-336.

[9] Vijayakumar B and Ashish Chaturvedi(2012)," Automatic Brain Tumors Segmentation of MR Images using Fluid Vector Flow and Support Vector Machine" Research Journal of Information Technology, vol.4, No. 3, pp. 108-114   .