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COMPARATIVE STUDY ON BRAIN TUMOR SEGMENTATION TECHNIQUES

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Abstract

This paper is an in-depth analysis of diverse methods used in segmenting Brain tumor images and measures the performance of three such methods. The role played by Brain Tumor Segmenting cannot be understated when it comes to diagnosing tumors and for developing treatment strategy. Generally in medical imaging, segmentation of brain tumor images is performed manually. It requires immense skill combined with expertise and experience. Apart from being time consuming, manual brain tumor delineation is complicated and depends on the individual operator. It is the focal disadvantages in this method. Hence more and more research is undertaken in all corners of the world to derive a method which will surpass all present disadvantages. Among many three methods are considered promising and an comparative study has been developed here. The first method segment the brain tumor image using Local Independent Projection based Classification (LIPC). The second method uses wavelet and Self Organization Map (SOM). Finally the third method applies graph cut segmentation approach to segment tumor from the given brain MRI image. To analyse the performance of these methods, several performance metrics are used. This paper utilizes Precision Rate, Recall Rate, F-Measure, Sensitivity and Specificity to analyses the performance. From the experimental results it is shown that the Wavelet based SOM method performs better than the other two methods.

Keywords: Brain MRI, Graph cut, Image segmentation, LIPC, Preprocessing, SOM.

I. INTRODUCTION

Segmentation of brain MR image is an extremely challenging and crucial task which is essential for the intention of diagnosing and treating brain tumors and other neurologic complaints. Brain tumors can be classified depending on their shape, size, location and image intensities. In certain types of tumor, for example, edema in Tumor, will lead to damage, deformities of nearest structures, additionally to the intensity properties of the nearby region. Glial tumor is the most typical and cancer-causing tumor type that has a high mortality rate in adults. Over 90% of all tumors in persons over twenty years are glial tumors [1]. They occur within the glial cells of the brain and exhibit a speedy growth by broadening into the healthy brain tissues. Segmentation of image plays a very vital role. Image segmentation is that the partition of an image into segments referred to as subsets or classes, based on one or more features or characteristics, and augmenting the areas of interest by separating them from the background and all other areas [2]. This is commonly carried out manually. Manual segmentation of brain MR images may be a time intense and exhausting procedure which will show variations once performed by distinct experts [3]. Segmentation of 1500 – 2000, 512 x 512 sized brain images takes regarding 2 to 4 hours [4] and it show 14-22% variations once carried out by different experts [3]. Robust computerized segmentation algorithms will facilitate physicians by examining tissues and structures in a quantitative manner to analyze and diagnose the brain ailments. Multiple factors hinder the brain segmentation, particularly tumor and edema may be a quite tough task because of the background noise, unclear boundaries, nonhomogeneous intensity distribution, complex shape and low intensity contrast between closest tissues of the brain [5]. Segmentation method is more intricate in the case of glial tumors because of the heterogeneous form of the tumor that consists necrotic and active part. The fact that not all glial tumors have a transparent boundary between active and necrotic parts, and which some might not have any necrotic elements additionally complicates segmentation [6].

There are numerous alternate strategies proposed for segmentation of brain image because of the inherent problem of detection and brain tissues quantification. [6]- [18]. There are studies that segment tissues of the brain into 3 components as white matter (WM), Grey matter (GM) and Cerebrospinal fluid (CSF) [7]-[11]. In spite of the fact that this can be useful for diagnosing several neurological complaints, segmenting pathological regions of brain is critical for the patients with edema and tumor. Studies which segment only tumor [12-17] and tumor and edema together [6], [18] use patient data with various type of tumors. Studies [6], [13], [14] performed segmentation with glial tumor in adults. Not at all like past studies that use wavelets and SOM, both pathological (tumor, edema) and healthy (GM, WM, CSF) tissues of the brain are segmented in this study. Neural networks (NN) carry out classification through learning from data and do not apply rule sets. NN can simplify using previous data and learn from past experience. They have benefits like tolerancing fault, learning by themselves and searching for the optimum. They execute well on extreme, variable, non-linear and noisy domains, such as segmentation of brain tissues, where it becomes more complicated to use rule-based systems or decision trees. SOM is a standout amongst the most prevalent NN which utilize an unsupervised competitive learning algorithm. SOM automatically coordinates itself according to the input data using a similarity factor such as Euclidean distance. Topological relationships of the SOM are preserved in the input and adjacent inputs are mapped to adjacent neurons [19].

Studies that use SOM must cluster the output of the network because it has more output neurons than the tissue types to be segmented. The similar output neurons are clustered by using an additional NN which uses weight vectors as input [8], [9] and [13]. Reddick et al. [8] proposed a strategy which utilizes a SOM method for segmentation and a multilayer back propagation NN for classification of the SOM output. This methodology exploits T1, T2 and proton density (PD) MR images to segment healthy brains into WM, GM and CSF. They utilized their seven labelled studies to train and the remaining seven to test the second NN. Each input vector of the classification network had an related manual classification, that corresponded to one of the intracranial tissue or background. Song *et al*. [9] combined weighted probabilistic NN to SOM. Their method implements SOM to excessively segment the T1 and T2 MR images. They estimated fractional contributions of each reference vector to several target classes and utilized the expert-picked training sets to compute a posteriori probabilities of the reference vectors belonging to each of the final target classes via Bayesian theorem. Their parametric methodology expect a probability density function (PDF) of the tissue which does not match real data distribution and lack accuracy.

Iftekharuddin *et al*. [13] used feed forward NN with automated Bayesian regularization as the classifier subsequent the SOM clustering. Low contrast-to-noise ratio or signal-to-noise ratio decreases the correct segmentation ratio in spite of of the method used [20]. The filtering methods which are space-invariant like low-pass filtering is applied to the images for a solution to this problem. The conventional filtering methods have the major drawbacks like blurring the object boundaries and important features, and suppression of fine structural details in the image, especially small lesions [21]. This drawback is resolved by the space-variant filters by utilising local and feature-dependent techniques. Examples of these filters are anisotropic diffusion filtering, local shape-adaptive template filtering,and linear least-squares error filtering. Gerig *et al*. [20] compared the non-linear anisotropic diffusion filter which is proposed by Perona and Malik [22] with a extensive range of filters used to eliminate the random noise of the MR image. They confirmed that the homogeneous regions are blurred by using anisotropic diffusion filter and the ratio of signal-to-noise regions is enlarged and also the object borders are sharpened. This filter also lowers the partial volume effects and decreases noise, thus greatly reducing subsequent operator-dependent errors in misclassified training points. [21] Accurate segmentation of the images relies on the automatic feature extraction methods which determine the best features to differentiate various tissues. Wavelet transform is used generally in feature extraction for segmentation of brain MR image, because it yields well localization in both spatial and spectral domains [13], [23]. As with every other method, even this has its limitations. But its drawback is the translation variant characteristics of discrete wavelet transform (DWT). This directs it to extract remarkably different features from the equivalent two images with only a small realignment [24]. Stationary wavelet transform (SWT) [25] is used to overwhelm this problem by eliminating the down-sampling procedure from the DWT and makes an over-complete representation. While all the images decomposed by SWT and the original image have the equal size, SWT coefficients and textural features that are extracted from them can be utilized directly for segmentation without a need for projection [26].

The rest of the paper is ordered as follows: The overview of first method is offered in Section II. The second method is specifically depicted, including its design idea and practical implementation approach in Section III. The overview of third method is presented in Section IV. The performance of the three methods is compared in Section V. Finally, conclusions are made in Section VI.

II. BRAIN TUMOR SEGMENTATION USING LIPC

The segmentation method explained in [4], uses LIPC, which is one of the recent works published. LIPC treats brain tumor segmentation as a classification problem. This classifies each voxel into different classes. In calculation of projection, locality is very important. To decrease the computational costs, this method is embedded in a multi-resolution framework.

This method contains four most important steps. They are A) Preprocessing B) Extraction of features C) Segmentation of tumor using the LIPC method, and D) Post processing. The flowchart of this method is demonstrated in Fig. 1.

A. Preprocessing

An essential step in segmentation is preprocessing, which in layman's term can be called as 'cleaning'. It is an filtering step where irrelevant and redundant data, whether noise or otherwise is removed. To improve the quality of visualization, Pre-processing is done on the image initially. After capturing the digital image and prior to instigating algorithm applications, each image should be assessed with regard to its general characteristics like noise, background, brightness, blur, intensity variations etc. This work is effectively completed through pre-processing step. In this analysis, all MRI image modalities are processed as follows.

The N3 algorithm is applied to take away the bias field artefacts from the images at first. Then the intensity values between 1% and 99% quantiles are computed for the brain region and then these two values are utilised to linearly scale the voxel intensities to the range [0,100].

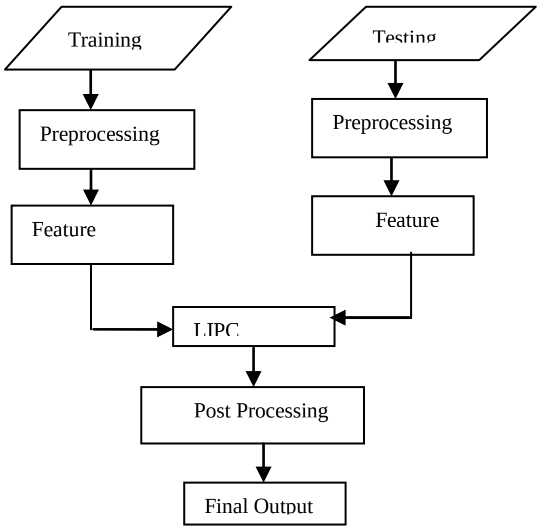

Fig1: Overall Flow Diagram of Local Independent Projection Based Classification method

B. Extraction of features

Extraction of features plays a very important task in segmentation of images. Feature Extraction is applied to get features that will be useful to classify and identify images. Here feature extraction is performed based on a patch based technique. First we obtain the intensity value in a patch around a voxel, v, and it is reorganized as a feature vector. Multi resolution frame is used to reduce Computational complexities and improve robustness.

C. LIPC method

The brain tumor segmentation can be well thought-out as a multiclass classification issue. To solve this issue, an OvA (One-Versus-All) approach can be used. In this approach, a classifier is trained per class to differentiate a

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class from all other classes. Hence, N classifiers f = {fi}Ni=1 have to be determined, in which N indicates the number of classes. Given a testing sample x€RM, N actual classification scores y={yi}i=1 N are calculated using the learned classifiers f(x) ; where the sample x indicates the features of the image in the current study yi € [0,1] stands for the probabilities that the sample belongs to the i^{th} class. The label of sample can be defined as: l=argmax fi (x) =arg max yi. Dictionary construction is carried out by using manually labeled original samples in a training set. As the number of original training samples generates large D, it increases the computational costs and memory. But it is necessary to apply a dictionary learning method for understanding a compact representation of the initial training sample. The k-means approach is used in this method. In order to achieve classification scores, Softmax regression model is used. By using learned as well as without learned softmax regression model, classification accuracy was tested. For real data groups (n<0.02), the learned softmax regression model contain the high accuracy value. But for synthetic data groups(n>0.6), the classification accuracy using both softmax regression model was found to be same. This illustrates that the intensity distribution is complex in real data groups than in synthetic data groups. In synthetic data including high-grade gliomas, the intensities of the three classes might be easily alienated, while the intensity dissemination of the three classes mainly coincided with one another in real data groups. The sharing of the training data in every submanifold provides essential details for the classification work. Also it will bring discriminative data while classifying a testing sample. Therefore for data with complex distribution, the learned softmax regression model was appropriate.

D. Post Processing

In this investigation and analysis, the classified edema region is post processed by using the hypothesis in which every edema region is positioned near core regions of tumor. According to this assumption, all classified edema region should have a voxel near the classified tumor regions within a small distance. Therefore, to improve the classified edema regions, the mathematical morphology and connected component algorithm can be used. Initially, a binary image which represents the classified edema regions is created. Afterwards, this binary image is utilized as an input for the connected component algorithm, and then some individual edema regions are formed. Next, every individual edema region is dilated with a small structuring element and compared against the classified tumor regions. Finally, the dilated edema regions which share at least a voxel with the classified tumor regions are considered as a valid region. From these valid regions, the edema regions are retained as the final edema classification results, while the other edema regions are discarded.

III. BRAIN TUMOR SEGMENTATION USING WAVELET AND SELF ORGANIZATION MAP

Wavelets are basically a wave like oscillation that begins with zero, increases or decreases in amplitude, and ends with zero. Self organization Map (SOM) is a popular neutral network model. SOM is build on unsupervised learning which means there is no need for human intervention and very less information is required regarding the characteristics of input data. In short, SOM can use for clustering the data with no knowledge about the class memberships of the input data. SOM could be used to detect features innate to the problem. This section is about how combining Wavelets and SOM for image segmentation results in hybrid feature extraction for analysis. The brain MR image datasets, materials and methods that are used to perform brain MR tissue segmentation algorithm are given discussed here. Flow diagram of the algorithm which disguises both testing and training processes are given in Fig.1. The steps which contain the implementation of the algorithm details are discussed in the following subsections.

A. Preprocessing

It is common knowledge that brain imaging is corrupted by noise during transmission and digitalization of images. The intensity range of the images is normalized to get the maximum value by dividing the intensity values. To enhance the signal to noise ratio, the anisotropic Diffusion filter is applied. The diffusion process is performed by using this filter. The inner parts of the regions are smoothed by using edge strengths and noise degradation statistics. The inner parts of the regions are smoothed by using edge strengths and noise degradation statistics and the edges are preserved by estimating local image structure.

B. Skull Stripping

In any imaging of the brain, Skull stripping is an inherent part. The thresholding and Morphological operations are combined to developed an algorithm that is used for skull stripping which is also known as whole brain segmentation. It removes the non-cerebral tissue like muscle, skull, skin, and connective tissues which are not the regions of interest. The steps in the process of skull stripping include Diffusion filters, Edge detection (the area between the brain and the skull) Finding brain, Extract brain and finally Tuning parameters.

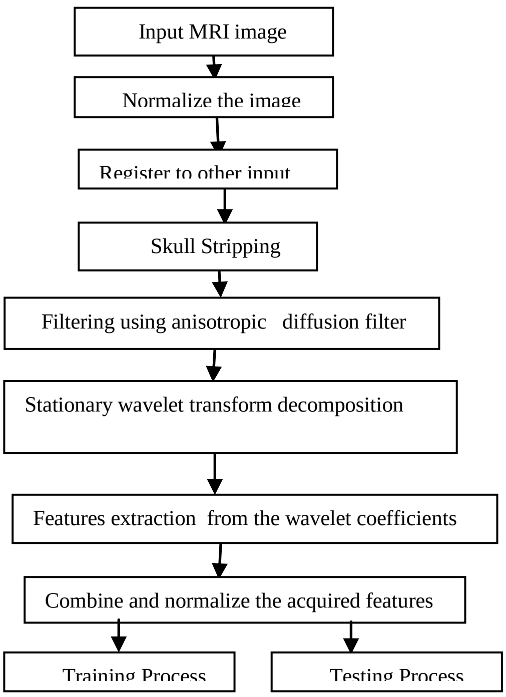

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Fig2: Overall Block Diagram of wavelet and self organization map

C. Feature Extraction

Stationary Wavelet Transforms (SWT) are exploited to extort features from the MR images which will be used as input to the Neural Network (NN). The SWT is a wavelet transform algorithm proposed to overwhelm the lack of translation-invariance of the Discrete Wavelet Transform (DWT) [3]. Even if the signal is shifted, the coefficients of SWT will not change. In a conventional wavelet transform, down sampling and convolution with a filter is used to the signals for decomposition. Decomposed signal is 1/2n in size, where n denotes the decomposition level. 2n pixels in the original signal are denoted by a pixel in the decomposed signal. As a result, for pixel based segmentation without projection, wavelet coefficients are not used. SWT has a fast iterative algorithm and utilizes an over complete decomposition which comprises a tight frame. Decomposition filter is upsampled and convolved with the signal to acquire the coefficients of the subsequent level. Unlike the traditional wavelet transform which downsamples the signal for decomposition of each level that implies the upsampling by a factor of *m*. Filters hi and gi are dilated by a factor of *2* by inserting proper number of zeroes between filter taps for each iteration.

D. SOM and Learning Vector Quantization (LVQ)method

SOM is used for the segmentation tool in this study. It is far trained to map the input image to the equal tissue regions consistent with their characteristic features. By using this mapping, the dimension and groups similar regions together are reduced which helps to understand the high dimensional image data. SOM consists of 2 layers. The primary layer contains input nodes and also the secondary layer contains output nodes that are in a two-dimensional grid format. There are adjustable weights between every and each output. A multidimensional observation is related to every unit. The map attempts to represent the features with best accuracy through a limited set of clusters. At the end of training process, the clusters become ordered on the grid. Therefore similar clusters are nearby and dissimilar clusters are remote from each other. During the training process, SOM clusters the data by having output units contend for the current input feature vector. As a result, the closest unit to the input becomes the successful unit or BMU (Best Matching Unit). Then the weight vectors of this and its neighbour units are updated. The supervised LVQ algorithm which uses the labelled data that is utilized for fine-tuning the weight vectors of the trained and labelled SOM. The purpose of LVQ is to depict the class regions in the input space by including similarly labelled codebook vectors into the classes still if there is an coincide of class distributions of the input samples at the class borders. To improve recognition accuracy, it is suggested to start learning with the LVQ1 algorithm which converges very fast and continue with the LVQ3 algorithm using a low initial value of learning. Thus, we used LVQ3 following the LVQ1 with learning rate of 0.5 and running length of 1000. We used 0.3 for relative learning parameter and 0.2 for window width parameter in LVQ3 algorithm.

IV. BRAIN TUMOR SEGMENTATION USING GRAPH CUT SEGMENTATION

Graph cut offers a flexible formulation for image segmentation. It affords a suitable method to encode regular local segmentation cues, and a collection of powerful computational methods that are used to extract global segmentation from this simple local pixel similarity. Computationally graph cuts can be very efficient. The method contains 3 main stages. They are 1) a content-based image retrieval approach for identifying training images (with masks) most similar to the patient brain using a partial Radon transform and Bhattacharyya shape similarity measure 2) Creating the initial patient-specific anatomical model of brain shape by using SIFT-flow for deformable registration of training masks to the patient brain 3) Extracting refined brain boundaries using a graph cuts optimization method with a customized energy function.

A. Shape Similarity for Brain database Using Content-Based Image Retrieval (CBIR)

Initially small subset of images is identified in the training database. This subset of training images will develop the patient particular brain model using CBIR. CBIR system is used to generate a ranked subset of images similar to the query which is a brain image of the new patient in our case. The brain database is pre-processed and contains the globally aligned and normalized brain.

The Orthogonal projection profiles or else Radon transforms are used to compare and rank the similarity between brain images of two patients. The Radon transform projection along an arbitrary line in the x-y plane is stated as

$$R(\rho, \theta) = \iint I(x, y)\delta(\rho - x\cos\theta - y\sin\theta)dx\,dy$$

The Radon transform calculates a projection of the image as a sum of line integrals accumulating pixel intensities. The partial Radon transform projection method is fast to compute and only an approximate matching atlas set of brain segmentations from the brain database is needed to compute a spatial prior which can be refined in the succeeding phase of the algorithm.

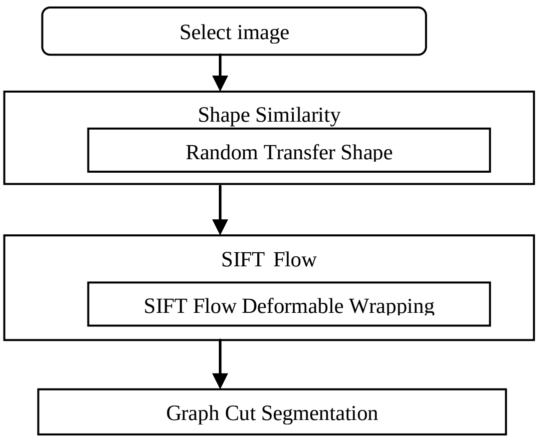

Fig.3. Overall block diagram of Graph Cut Segmentation

B. Scale Invariant Feature Transform (SIFT Flow non-rigid Registration)

The SIFT features of the brains are computed as follows. Initially, the gradient orientations and magnitudes are computed at each pixel. The gradients are weighted by using a Gaussian pyramid. The regions are divided into quadrants. To form a gradient orientation histogram, the gradient values are added to one of eight orientation histogram bins in each quadrant. The orientation histograms of the quadrants are concatenated to form the SIFT descriptor vector which are obtained from the center pixel of the region. Once we have estimated the SIFT features for the image pair, the registration algorithm calculates pixel-to-pixel correspondences by matching the SIFT descriptors.

C. SIFT Features Extraction

SIFT is an algorithm in computer vision to detect and describe the local features in images. Applications include objectrecognition, 3Dmodeling, gesture recognition, navigation, image stitching, robotic mapping, video tracking, individual identification of wildlife and match moving. Initially SIFT key points of objects are extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually associating each feature from the new image to this database and retrieving the candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of key points that agree on the object and its orientation, location, scale in the new image is identified to filter out good matches. The determination of consistent clusters is carried out rapidly by using an efficient hashtable implementation of the generalized Hough transform.

D. Graph Cut Segmentation

A wide ranging of low-level computer vision problems like stereo correspondence problem, image smoothing and other computer vision problems which can be expressed in terms of energy minimization are solved using Graph Cut method. These types of energy minimization problems can be reduced to instances of the maximum flow problem in a graph. Under most formulations of these problems in computer vision, the minimum energy solution corresponds to the maximum a posteriori estimate of a solution. Even if many computer vision algorithms involve cutting a graph, the term "graph cuts" is applied particularly to that model which employs a max-flow/min-cut optimization.

V. PERFORMANCE ANALYSIS

A. Experimental Images

Experiments were conducted on a set of color images to prove the efficiency of the proposed scheme. For the experimental purpose, some standard 512 × 512 cover images are taken. Some of the brain MRI images are exposed in Figure 4.

B. Performance Analysis

To estimate the performance of these three methods, several performance metrics are available. This paper utilizes the Precision Rate, Recall Rate, F-Measure, Sensitivity and Specificity to analyses the performance.

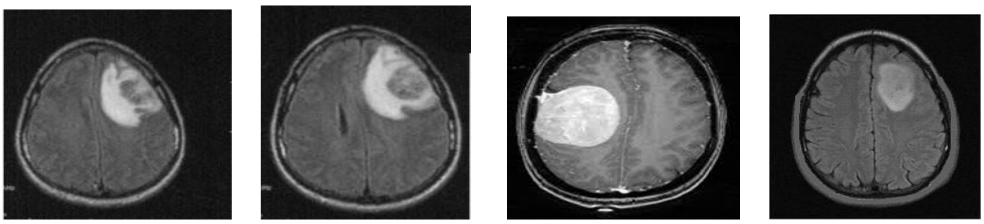

Fig.4.Brain MRI images

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4.1 Precision Rate

The precision is the fraction of retrieved instances which are relevant to the find.

$$Precision = \frac{TruePositive\,(TP)}{TruePositive\,(TP) + FalsePositive\,(FP)}$$

Where TP = True Positive (Equivalent with Hits)

FP = False Positive (Equivalent with False Alarm)

4.2 Recall Rate

The recall is the fraction of relevant instances which are retrieved according to the query.

$$Recall = \frac{TruePositive\,(TP)}{TruePositive\,(TP) + FalseNegative\,(FN)}$$

Where TP = True Positive (Equivalent with Hits)

FP = False Negative (Equivalent with Miss)

4.3 F-Measure

F-measure is the ratio of product of precision and recall to the sum of recall and precision. The f-measure can be calculated as,

$$F_m = (1 + \alpha) * \frac{Precision * Recall}{\alpha * (Precision * Recall)}$$

4.4 Sensitivity

Sensitivity also called the true positive rate or the recall rate in some fields measures the proportion of actual positives.

$$Sensitivity = \frac{TruePositive}{(TruePositive + FalseNegative)}$$

Where, TP – True Positive (equivalent with hit)

FN – False Negative (equivalent with miss)

4.5 Specificity

Specificity measures the proportion of negatives which are correctly identified such as the percentage.

$$Specificity = \frac{TrueNegative}{(FalsePositive + TrueNegative)}$$

Where, TN – True Negative (equivalent with correct rejection)

FP – False Positive (equivalent with false alarm)

To analyse the performance of the proposed system, it is associated with several techniques by using the performance metrics which are mentioned above. This is shown in the below tables and graphs.

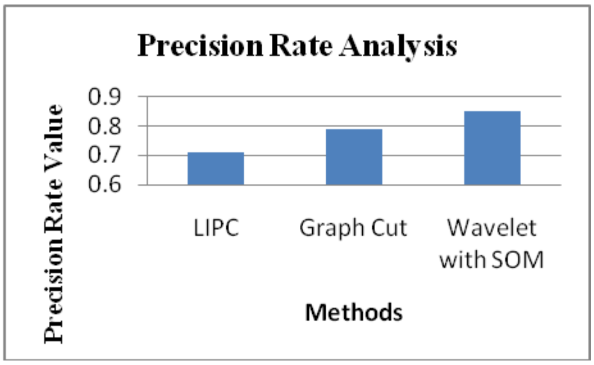

Fig.5. Precision Rate Analysis

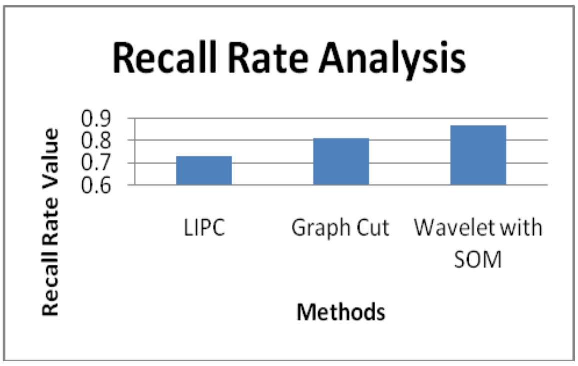

Fig.6. Recall Rate Analysis

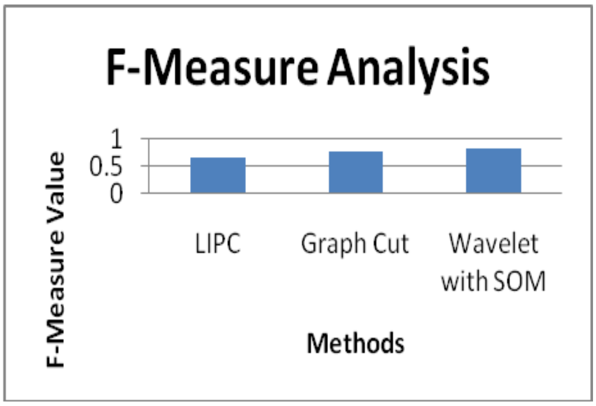

Fig.7. F-Measure Analysis

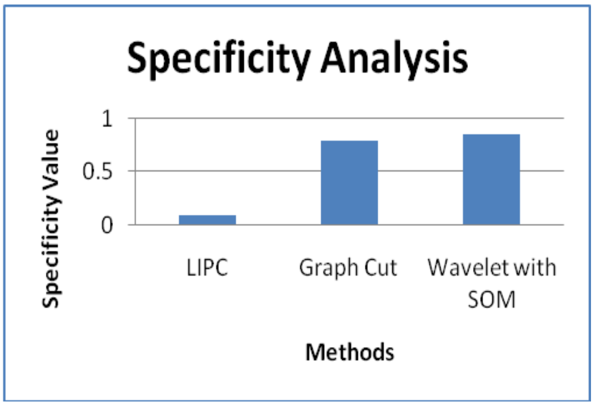

Fig.8. Sensitivity Analysis

VI. CONCLUSION

After a comparative review analysis, it can be safely said that Wavelets combined with SOM is better than the other two methods reviewed. For instance, Graph cut method has shrinking bias, the algorithm can be subjective for creating a small contour. It may overlook segmentation of thin objects like blood vessels. Moreover, Graph cut method is basically a binary labeling procedure. When it comes to LIPC method, this region based method correctly segments regions, but it is quite expensive in terms of computation of both time and memory. As of the experimental results of performance analysis, it is clear that the Wavelet based SOM approach performs better than the other two methods.

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