Fast and Accurate Brain Image Retrieval Using Gabor Wavelet Algorithm

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***Abstract*— CBIR in medical image databases are used to assist physician in diagnosis the diseases and also used to aid diagnosis by identifying similar past cases. In order to retrieve a fast, accurate and an effective similarity of images from the large data set. The pre-processing step is extraction of brain. It removes the unwanted non-brain areas like scalp, skull, neck, eyes, ear etc from the MRI Head scan images. After removing the unwanted areas of non-brain region, it is very effective to retrieve the similar images. In this paper it is proposed a brain extraction technique using fuzzy morphological operators. For the experimental results 1200 MRI images are taken from scan centre and some brain images are collected from web and these have been implemented with popular brain extraction algorithm of Graph-Cut Algorithm (GCUT) and Expectation Maximization algorithm (EMA). The experiment result shows that the proposed algorithm fuzzy morphological operator algorithm (FMOA) is prompting the best promising results. Using this FMOA result retrieved the brain image from the large collection of databases using Gabor-Wavelet Transform.**

Keyword- Fuzzy morphological operator, T1-weighted MRI, Gabor-Wavelet Transform.

I. Introduction

The medical and related health professions use and store visual information in the form of X-rays, CT scanned images, MRI scanned images, for diagnosis and monitoring purposes. In this paper, we used MRI head scan image. The extraction of brain from MRI head scans plays an important role for pathological studies in medical applications. Content-based image retrieval (CBIR) method contains the visual content in image data. Images have rich in visual contents like color, shape, texture etc. The visual contents like color, texture and shape are more or less same for all brain images. In order to get the fast, accurate and effective retrieval of images we have to remove the unwanted non-brain areas like scalp, skull, neck, eyes, ear etc. This method is called Brain Extraction technique. Here this technique is considered as pre-processing work. There are several Brain Extraction algorithms have been developed and are used in many research. Here, it is proposed to use a Brain extraction technique using fuzzy morphological operators. By using automatic threshold value, we get the binary image. Then this binary image is labelled using the connected component. Here we classified binary image into three connected component regions. The histogram is applied to this three connected components and the minimum histogram value gives the rough portion of the brain image. Fuzzy morphological operations are then performed on the rough brain portion of the image to get the fine brain portion. This proposed work implements the system on the basis of 2 phases.

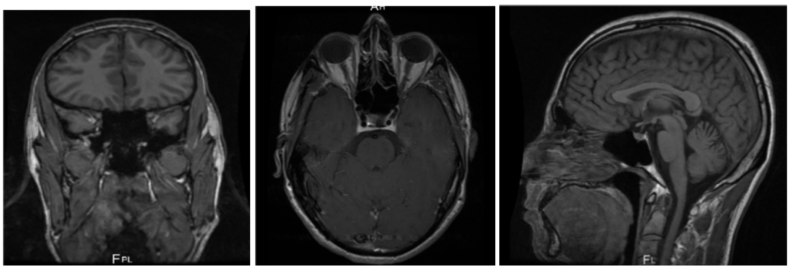
Phase-1: Pre-Processing work i.e. extraction of fine brain portion using fuzzy morphological operator.

Phase-2: From the output of Phase-1, Retrieval of brain images from the large data set using Gabor-Wavelet Transform.

This paper is organized as follows. Materials and methods are implemented in section II which briefly describes the proposed frame work. Results & discussions are presented in section III. Finally conclusions arrived at are given.

II. MATERIALS AND METHODS

The T1 weighted brain image can also be taken in three orientations, axial, coronal and sagittal as in Fig 1. The axial orientation of the MRI head image is viewed from neck to head. The coronal orientation begins at the tip of the nose and ends at the back of the head. The sagittal orientations are from ear to ear. By interpreting these various types and contrast that are produced, a radiologist or other physicians can help to make diagnosis of medical conditions.



(a) (b) (c)

Fig 1. Types of MRI orientation on T1 –weighted images
(a) Coronal (b) Axial (c) Sagittal

A. Pre-Processing Work (Phase 1)

Some of the popular Phase-1 Brain Extraction Algorithm's are watershed algorithm [1], statistical parameter mapping (SPM2) [2],brain surface extractor (BSE) [3], brain extraction tool (BET) [4], Minneapolis, brain extraction meta algorithm (BEMA) [6], hybrid watershed algorithm (HWA) [7], model based level sets (MLS) [8], adaptive brain segmentation (ABS) [9], region growing method [10] and graph cut method (GCUT) [11]. The numbers of previous work have been done for extracting brain portion from MRI head image. The outcome of existing system does not work accurately for all types of MRI scans and it is restricted to specific orientation or datasets are forced the user in the basis of either processing speed or accuracy. In this paper the trial of implementing in MRI brain image using fuzzy morphological operators [5] gives the promising results. System architecture of Phase 1 is given in Fig 2.

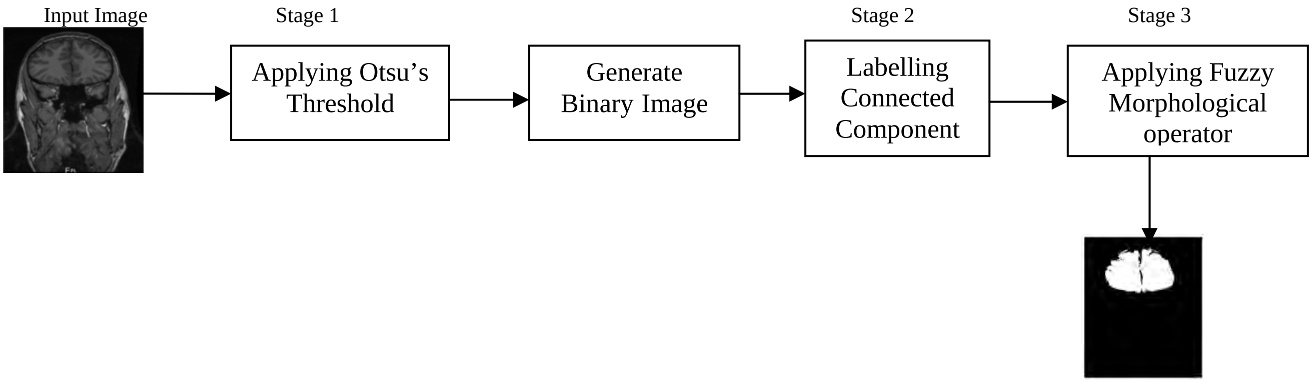


Fig 2. System architecture of Phase 1

The Pre-processing work consists of 3-Stage system to get fine brain portion.

Stage 1: Applying of Otsu's Threshold algorithm.

Stage 2: Labelling the largest connected component.

Stage 3: Applying of Fuzzy Morphological operations.

1) Applying of Otsu's Threshold Algorithm (Stage 1)

In Stage 1, two steps are being followed as given below:

(i) Threshold creation using Otsu.

(ii) Binary image creation using Otsu Threshold value is 0.1725

(i) Threshold creation using Otsu

Otsu's method is used to automatically convert the gray level image to a binary image. It is a simple tool for separating the objects from background. Each individual pixel in an image is marked as "object" pixels if their value is greater than some threshold value. Here, in this work, 0.1725 is used as a threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. Normally, an object pixel is given a value of "1" while a background pixel is given a value of "0." Finally, a binary image is created by coloring each pixel white or black, depending on a pixels label.

(ii) Binary image creation using Otsu Threshold

In the Otsu threshold technique image is partitioned into two classes namely C_1 and C_2 at intensity level t such that $C_1 = \{0,1,2,....t\}$ and $C_2 = \{t+1, t+2, t+3,...., N-1\}$ where N is the total number of intensity levels of the image.

Algorithm:

1. Compute histogram and probabilities of each intensity level. Let the number of pixels is at the i^{th} intensity level be n_i and n be the total number of pixels of the image. Then the probability of intensity level t is $p_i = \frac{n_i}{n}$.
2. Compute the probability of two classes C_1 and C_2 are ω_1 and ω_2

   $$\omega_1 = \sum_{i=0}^{t} p_i \quad \text{and} \quad \omega_2 = \sum_{i=t+1}^{N-1} p_i .$$
3. Calculate the mean of two classes:

   $$\mu_1(t) = \sum_{i=0}^{t} \frac{ip_i}{\omega_1(t)\mu_2(t)} \quad \text{and} \quad \mu_2(t) = \sum_{i=t+1}^{N-1} \frac{ip_i}{\omega_2(t)}$$
4. Assume $\sigma_B{}^2$ and $\sigma_T{}^2$ be the between class variance and total variance. The threshold value $thresh$ is obtained by maximization between class variance.

   $$thresh = \max\left(\frac{\sigma_B{}^2}{\sigma_T{}^2}\right),$$

   where $\sigma_B{}^2 = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2$ and $\sigma_T{}^2 = \sum_{i=0}^{N-1} (i - \mu_T)^2$.

   The total mean of whole image $\mu_T = \sum_{i=0}^{N-1} ip_i$.

Otsu Threshold algorithm is applied to Fig 1 and generating binary image is shown in Fig 3

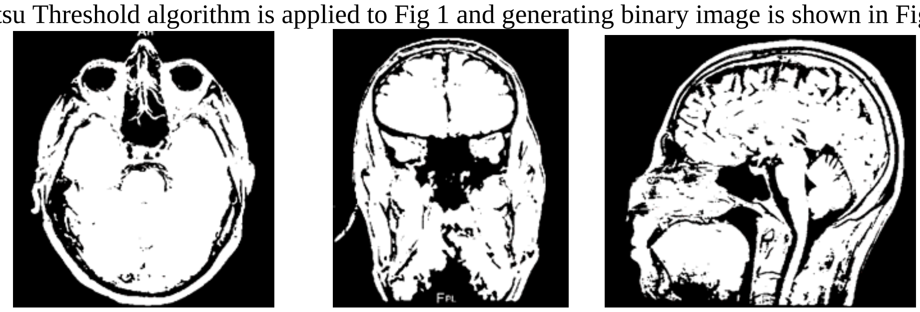
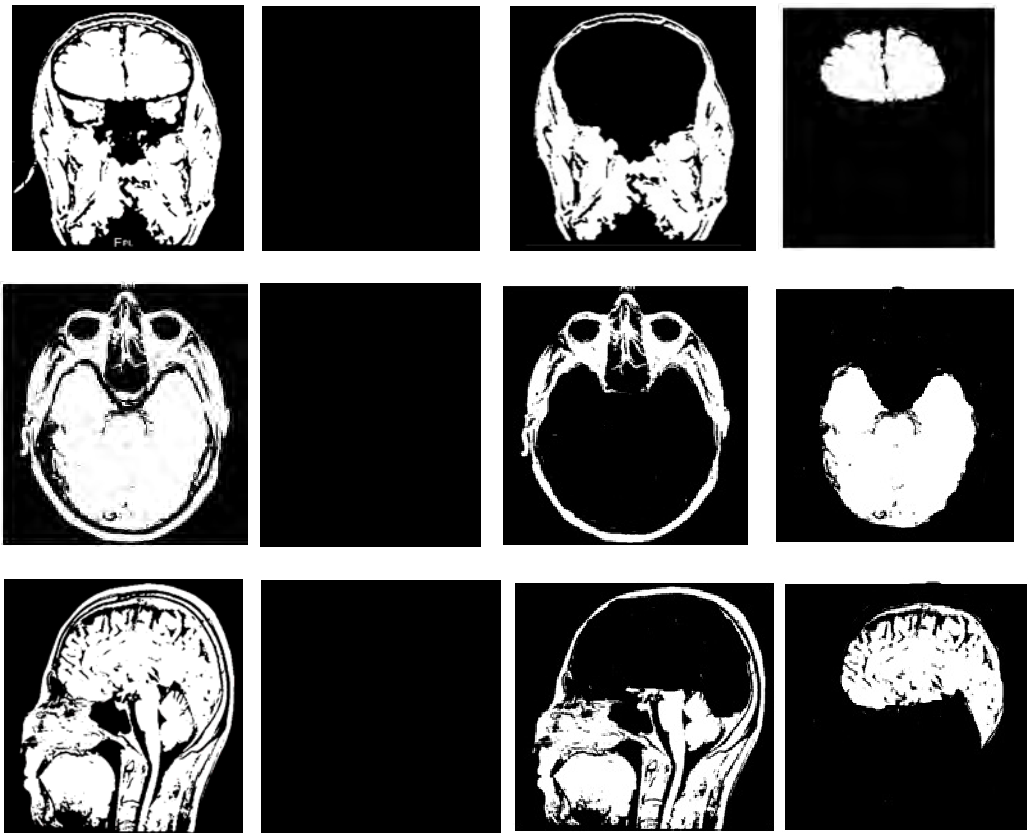


Fig 3. Generation of binary image

2) Labeling the largest connected component(Stage 2)

Connected-component labelling is used to detect connected regions in binary images. It works by scanning an image, pixel-by-pixel (from top to bottom and left to right) in order to identify connected pixel regions, *i.e.* regions of adjacent pixels which shares the same set of intensity values . Here the threshold image is labelled as input and 4-connectivity. Any pixel $p(x, y)$ has two vertical and two horizontal neighbours, given by $(x+1, y), (x-1, y), (x, y+1), (x, y-1)$

Getting the rough brain portion of the image it is marked as label 2. Already the binary image has two labelled with the values of 0's and 1's. Together with this we get 3-Labeled image. Label 0 is dark, Label 1 is white and Label 2 is gray. The sample labelling binary image is shown in Fig 4.



(a) (b) (c) (d)

Fig 4. Sample labelling of binary image

(a) Binarized Image (b) Label 0 (c) Label 1 (d) Label 2

Using this 3-Labeled image, to get rough brain portion applying the histogram for each and every labelled of the image. From that histogram values the minimum value gives the rough brain portion of the brain image.

3) Applying of Fuzzy Morphological operators. (Stage 3)

To produce a fine brain portion from the rough brain portion, fuzzy morphological operators are used. Commonly the fuzzy morphological operators are the opening and closing. Here the closing operator is used. For a binary image, white pixels are normally taken to represent foreground regions, while black pixels denote background.

Closing operator:

The closing operator is defined as dilation followed by erosion using the same structuring element for both operations. Dilation is the dual of erosion i.e. dilating foreground pixels is equivalent to eroding the background pixels with a 4x4 structure element (disc based). Implementation of closing operator needs 2 processing steps.

(i) Binary Erosion

(ii) Binary Dilation

Algorithms:

Calculation of Binary Erosion:

1. Read the binary image as B_{img} .

2. Choose the size of the structuring element SE as $M \times N$. Here 4×4 (disc based) is used.

3. Do the following steps in each pixel of the B_{img} .

(i). Get the pixel say $B_{img}(i, j)$.

(ii) Select the neighbouring pixels of $B_{img}(i, j)$ using SE value of $M \times N$ and take is as $W(i, j)$.

$$W(i,j) = B_{img}\left[i - M : i + M,\ j - N : j + N\right]$$

(iii) Find the minimum value of $W(i,j)$ and store the minimum value in E_{img} .

$$E_{img} = \min(W(i,j))$$

(iv) Replace all the pixel values of the window by E_{img} .

$$W(i,j) = E_{img}$$

Calculation of Binary Dilation:

1. Take the $W(i,j)$ values as input for dilation process.
2. Choose the same structuring element SE for that process also.
3. Do the following steps in each pixel of $W(i,j)$.

(i). Get the pixel of $W(i,j)$ and selecting the neighbouring pixels of $W(i,j)$ using SE Value of $M \times N$ and take it as $V(i,j)$.

(ii) Find the maximum value of $D_{img} = \max(V(i,j))$

(iii) Replace all pixel values of the window by D_{img} .

$$V(i,j) = D_{img}$$

Thus the closing operation closes small holes in the binary image, and fills narrow gaps in or between the connected components. By this way the fine brain portion of the image is being obtained.

B. Retrieval of Brain Image (Phase 2)

The term CBIR describes the process of retrieving desired images from the large collection of database on the basis of features that can be automatically extracted from the images themselves. The features include texture, color, intensity and shape of the object inside an image. Here the retrieval of brain images using texture as the feature. It involves two processes viz Feature Extraction process and Feature matching processes i.e retrieval of brain image. For the feature extraction process our previous work has been done by Color Histogram, Gabor and Wavelet transform. Similarly for the feature matching process our previous work has been done by using distance metric measures like Euclidean distance, Chi-Square distance, weighted Euclidean distance. From our previous analytical study Wavelet transform retrieve the image at very fast compared it with other techniques; but gives the better performance. But Gabor transform takes much time but gives the best result [12]. In our proposed system we used Gabor-Wavelet Transform for feature extraction technique. It is a two dimensional function with a multiscale partial differential operator of a given order. So it is a fast implementation technique. Gabor wavelets are used here to detect edges, corners and blobs. We apply a wavelet transform based on the Gabor kernel

$$\psi j\left(\vec{x}\right) = \frac{k^2{}_j}{\sigma^2} e - \frac{k^2{}_j}{2\sigma^2}\left(e^{i\vec{k}_j\vec{x}} - e^{-\frac{\sigma^2}{2}}\right) ------------------(1)$$

Where

$$\vec{k}_j = \begin{pmatrix} k_v \sin\phi_\mu \\ k_v \sin\phi_\mu \end{pmatrix}, k_v = 2 - \frac{v+2}{2\pi}, \phi_\mu = \mu\frac{\pi}{8} ------------------(2)$$

All the Gabor wavelets are created from this kernel by dilation and rotation. We design a Gabor wavelet for 4 scales and 5 orientations i.e scales $\mathbf{v}\boldsymbol{\epsilon}\{\mathbf{0},\dots\dots,\mathbf{3}\}$ and $\boldsymbol{\mu}\boldsymbol{\epsilon}\{\mathbf{0},\dots,\mathbf{4}\}$ (orientation). We have conducted retrieval test on brain images. Here we define the angle by 15, 45, 75,135 and 180 respectively and the wavelengths are 60, 80,120 and 130. For the first wavelength 60 we calculate for the 5 orientations, like 15, 45, 75, 135 and 180. Then for the 2nd wavelength 80 we calculate for the 5 orientations like, 15, 45, 75,135 and 180 and so on. After applying the Gabor filter, we extract the texture features of image by using standard deviation function. Then retrieving the image from the dataset we calculate the distance metric measures for every image. The minimum distance value signifies an exact match with the query.

For retrieve the similarity medical image form the large medical image dataset we used the distance metric measure. The distance metric is a function which defines the distance between two images. Here we used the distance metric measures as Euclidean Distance,[13], The formula of Euclidean distance is

$$D = \sqrt{\sum (x_i - y_i)^2} ----------------- (3)$$

The minimum distance value signifies an exact match with the query. For example a distance of 0 signifies an exact match with the query.

III RESULTS & DISCUSSION

In order to quantify the algorithmic performance of the proposed method on a MRI brain image, 1200 images of combinations of axial coronal and sagittal from different sources like scan centre are taken, some images are from IBSR web service developed by CMA at Massachusetts General Hospital and the whole brain atlas. To ease the work of testing and analyzing the images a graphical user interface (GUI) was developed using Matlab. It consists of two main panels, one is for Brain Extraction technique and another one is for the Brain Retrieval using Gabor-Wavelet Transform. The result of Brain Extraction is shown in Fig 5. The result panel of Brain Retrieval is shown in Fig 6. This algorithm is evaluated by four parameters like Sensitivity (SE), Specificity (SP), Positive Predictive Value (PPV), and Negative Predictive Value (NPV).

$$SE = \frac{TP}{TP + FN} ----------------- (4)$$

$$SP = \frac{TN}{TN + FP} ----------------- (5)$$

$$PPV = \frac{TP}{TP + FP} ---------------- (6)$$

$$NPV = \frac{TN}{TN + FN} ---------------- (7)$$

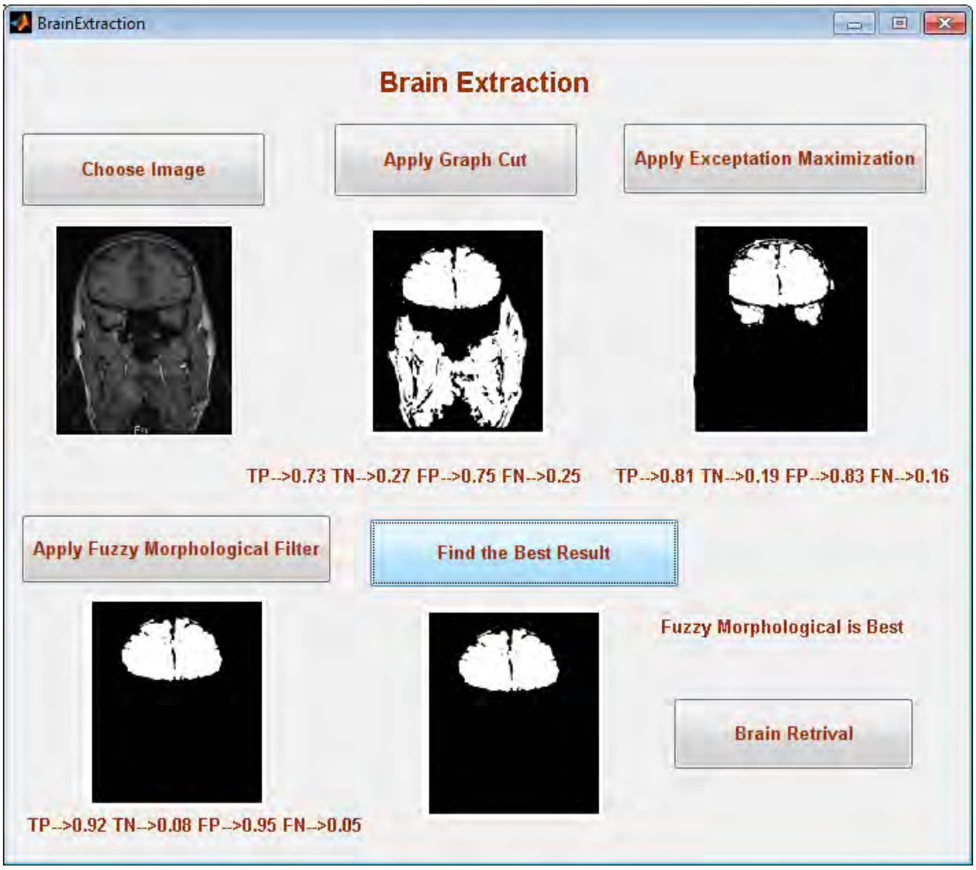


Fig 5. Result of Brain Extraction

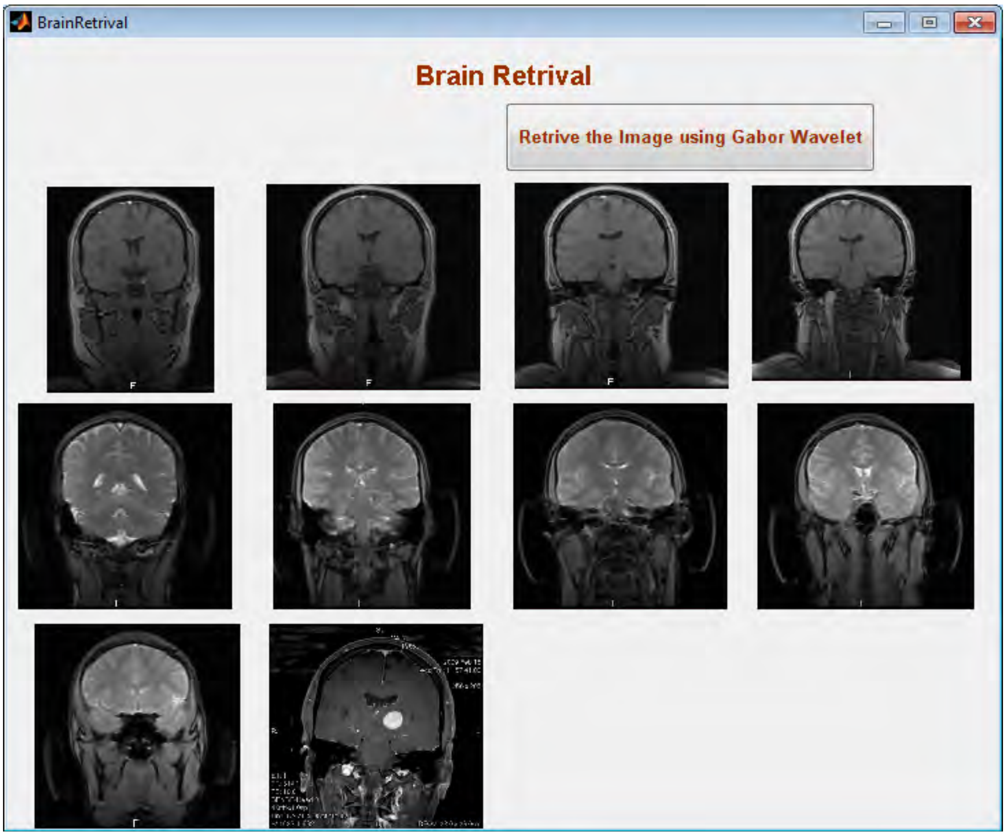


Fig 6. Result of Brain Retreival

SE, SP metrics are the ratio of extraction of brain pixels and unwanted Non-brain pixels, respectively. PPV is the ratio of pixels extracts the exact parts of the brain. NPV is the ratio of pixels extracting the unwanted non-brain parts. The quantitative metric measures are evaluated from the Eq.(4), Eq.(5), Eq.(6), Eq.(7) are shown in the Table 1.

TABLE 1 QUANTITATIVE MEASURES

Metric Measures	**Graph Cut Algorithm**			**Expectation Maximization**			**FMOA(Proposed)**		
	Axial	**Coronal**	**Sagittal**	**Axial**	**Coronal**	**Sagittal**	**Axial**	**Coronal**	**Sagittal**
SE	0.73	0.74	0.77	0.81	0.83	0.82	0.92	0.93	0.95
SP	0.25	0.26	0.21	0.16	0.17	0.14	0.05	0.07	0.04
PPV	0.49	0.49	0.49	0.49	0.49	0.49	0.48	0.49	0.49
NPV	0.48	0.51	0.47	0.47	0.54	0.44	0.69	0.62	0.68

From this the experiment result shows that the proposed method fuzzy morphological operator algorithm (FMOA) is prompting the best promising results Brain Extraction algorithm (Phase-1). The T1 weighted brain image can also be taken in three orientations, axial, coronal and sagittal and their implementations using brain extraction algorithm like Graph cut, Expectation Maximization and fuzzy morphological algorithm are shown in the comparison chart as in Fig 7.

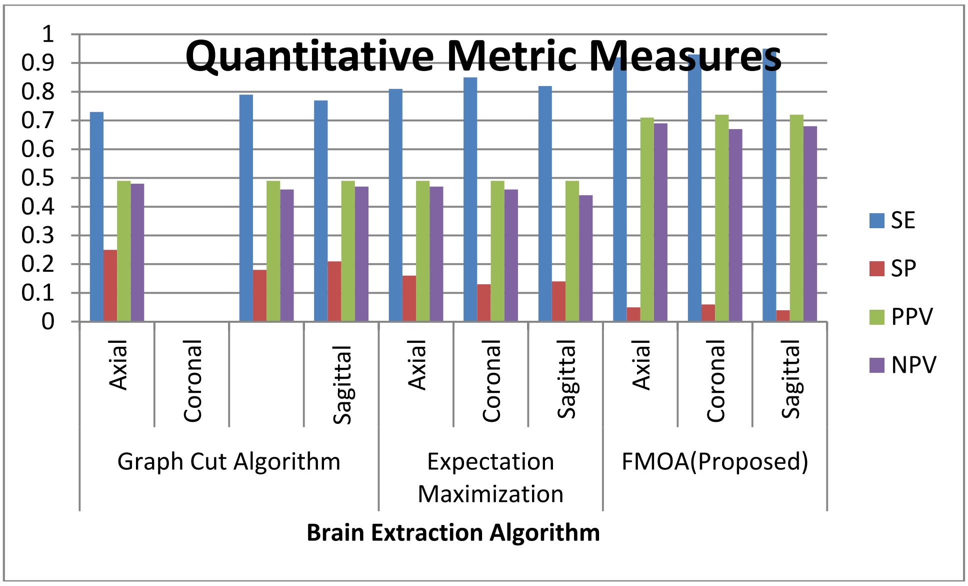


Fig 7. Comparison of Brain Extraction Algorithm

IV CONCLUSION

In this paper we have proposed fuzzy morphological operator algorithm with closing operator for brain extraction of T1-weighted brain image with three different orientations like axial, corona and sagittal and which gives the best result compare it with already existing algorithm. These method remove the unwanted non-brain areas like scalp, skull, neck, eyes, ear etc from the MRI Head scan images gives the speed and accuracy of diagnosis methods. For the retrieval of brain image from the large dataset Gabor-Wavelet gives the best result. In the future work is doing to extract the fine brain portion with other feature of the MRI image and also retrieval will also be done by another algorithm to get improvements of this proposed method.

ACKNOWLEDGEMENT

The authors would like to thank Mr. Chandraraj , Radiologist and Dr. Praveena Lionel Isabel's hospital, Chennai for providing MRI scan brain image the anonymous reviewers for their thorough reviews, and constructive suggestions which significantly enhance the presentation of the paper.

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