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HYBRID SEGMENTATION FRAMEWORK ON BRAIN TUMOR DETECTION IN MEDICAL IMAGES

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ABSTRACT

Brain tumor is an intracranial mass made up by abnormal growth of tissue in the brain or around the brain that limits its functionalities. Brain tumor diagnosis can be quite difficult because of its diversity in shape, size, and appearance and as a result, finding accurate measurement to its diagnosis can as well be critically difficult. This study developed hybrid segmentation framework for brain tumor images in medical imaging through the fusion of threshold and watershed approaches as the hybrid segmentation framework. The image was preprocessed using the Gaussian filtering technique for filtration. Enhancement was achieved using the image enhancement technique of MATLAB. The performance of the hybrid algorithm was evaluated based on Accuracy, Precision, Recall, F-measure, G-measure and False Alarm Rate. A comparative analysis was done to compare the hybrid, watershed, and threshold approaches based on the performance measure. The hybrid framework was found to perform better for all the performance measures with the accuracy value of 0.8250, precision value of 0.8889, recall value of 0.8571, F-measure value of 0.8729, G-measure value of 0.8729 and the false Alarm rate value 0.2500. Hybrid image segmentation framework was effective compared to watershed and threshold approaches and it is recommended for brain tumor analysis in medical image based on high value of accuracy.

Keywords: Image Segmentation, Medical Imaging, Digital Image Processing, Noise, Over Segmentation, Under Segmentation

INTRODUCTION

Brain tumor is an abnormal growth of cell inside the brain cranium which limits the functionality of the brain. Brain tumor diagnosis is quite tedious due to its diverse shapes, sizes, locations and appearance of tumor in the brain and as a result finding accurate measurement to its diagnosis can as well be difficult. Brain tumor had led to the death of many. Vipin and Seema (2015) stated that tumor of the brain develops because of unusual cell growth within the brain. Brain tumor generally can be classified into two types; benign and malignant tumor. Benign tumors are less harmful than malignant tumors as malignant are fast developing and harmful while benign are slow growing and less harmful. Most tumors (including brain tumor) are life threatening. Primary brain tumor originates in the brain. In the secondary type of brain tumor, the tumor expansion into the brain results from other parts of the body. Tumors can grow abruptly causing defects in neighboring tissues also, which gives an overall abnormal structure for healthy tissues according to (Anam and Tehseen, 2012). Correct segmented results are very useful for analysis, prediction, diagnoses and imaging tumors with more accuracy place vital role in the diagnosis of tumors. Segmentation employs high resolution techniques. According to Vipin and Seema (2015), image processing techniques have four distinct fields of actions: image analysis, image synthesis, image coding, image enhancement and restoration.

Image segmentation is an image processing technique in image analysis that divides an image into regions or categories which corresponds to different objects or parts of object (Abirani and Sheela, 2014). They also mentioned it to be an image processing technique to partition a digital image into multiple segments that is more meaningful and easier to analyze. The goal of image segmentation is to cluster pixels into salient image regions. Each of the pixels in a region is similar with respect to some characteristics or computed property such as color, intensity or texture. Generally, texture or pixel intensity may be characteristics on the basis of which this partition is carried out. Segmentation techniques are based on the three basic properties of intensity values which are discontinuity concept, similarity concept and statistical approach. The techniques can be classified into four general categories which are pixel-based technique, region-based technique, edge-based technique and model-based technique. Medical imaging is the technique and process used to create image of human body for clinical purposes or medical sciences. Imaging refers to several different technologies that are used to view the human body in order to diagnose, monitor or treat medical conditions. Medical image segmentation processes and analyzes medical images in order to extract meaningful information such as volume, shape, motion of organs, to detect abnormalities and to quantify changes in follow- up studies (Huang and Tscehperoakis, 2009). The primary objective of segmentation of medical images is to discover previously unseen or unnoticed information from an originally imputed image. Medical image computing focuses on the computational analysis of the images and not their acquisition.

Conceptual Review on Image Segmentation

Image segmentation is the partition of an image into regions or categories, which corresponds to different objects or parts of objects. The process of image segmentation is applied on grey scale or color digital images to generate compact, non-over-lapping, discrete and semantically meaningful partition out of the image (Rupanka and Samarjeet, 2014). Krishna and Akansha (2010) identified the result of image segmentation to be a set of segments that collectively cover the entire image or a set of contours extracted from the image. Abirami and Sheela (2014) classified the four general categories of segmentation techniques.

These techniques are…. Pixel- based technique is the simplest approach used for segmentation. Using this technique each pixel is segmented based on grey- level values that is pixels are allocated to categories according to the range of values in which a pixel lies, no contextual information is required only histogram. The region- based technique operates iteratively by grouping together pixels which are neighbors and have similar values and splitting group of pixels which are dissimilar in value. In edge- based technique, an edge filter is applied to the image, pixels are classified as edge or non-edge depending on the filter output and pixels which are not separated by an edge are allocated to the same category. Model-based technique is used when the information gathered from local neighborhood operators is not sufficient to perform the task, a specific knowledge about the geometrical shape of the objects is required which can then be compared with local information as well as image segmentation as it is typically used (Feng and Xinanghua 2013).

Image Pre-processing Techniques

Since most of the real-life data are noisy, inconsistent and incomplete, preprocessing becomes necessary because the presence of noise and low contrast edges -can affect the result of the segmentation. Satheesh and Prasad (2011) stated that noise removal is essential in medical imaging applications in order to enhance and recover fine details that may be hidden in the data. Image preprocessing is one of the preliminary steps which are highly required to ensure high accuracy of subsequent image analysis steps. Anithadevi and Perumal (2015) mentioned several de-noising/pre-processing approaches which are:

i. Gabor Filters: Is a linear filter used for edge detection and it has been found to be particularly appropriate for texture representation and discrimination.
ii. Adaptive Filters: Is developed for impulsive noise reduction of an image without the degradation of an original image.
iii. Morphological Operations: Makes use of fundamental operations which are erosion and dilation. Erosion removes small scale details from a binary image but simultaneously reduces the region of interest. Dilation uses structuring element for probing and expanding the shapes contained in the input image. Dilation is less destructive than Erosion.
iv. Mean Filters: Mean filtering replaces each pixel value in an image with the mean value of its neighbors including itself. This has effect of eliminating the pixels values which are unrepresentative of their surroundings.
v. Image Normalization: Is a process that changes the range of pixel intensity values. It is sometimes called contrast stretching or histogram stretching.
vi. Histogram Equalization: Is a method that usually increases the global contrast of many images. Histogram allows areas of lower local contrast to gain higher contrast by spreading out the most frequent intensity values. This method is suitable for images where both background and foreground are dark or bright.
vii. Weighted Median Filter: Has noise attenuation capability, robustness and edge preserving capability, robustness and edge preserving capability of classical median filter.
viii. Weiner Filter: Is a type of linear Filter and has been used for the restoration of noisy and blurred images.
ix. Contrast Agent Accumulation Model: Improves only the contrast of the images and unwanted tissues are not eliminated.

Some filters are best for de-noising medical images, Arin et al (2014) had identified the filters to be as follows:

i. Average Filtering: Is useful for removing grain noise from a photograph. Because each pixel gets set to the average of the pixels in its neighbourhood, local variations caused by grain are reduced.
ii. Gaussian Filtering: Is considered as a type of linear filtering. In frequency domain, blurring is achieved by attenuating a specific range of high frequency of image as such as the Gaussian filter was used. It has more ability to remove noises than other filters.
iii. Log Filtering: Is a laplacian filter with a Gaussian filter, this filter does not acceptably affect noise.
iv. Median Filtering: The value of an output pixel is determined by the median of the neighborhood pixels rather than the mean.
v. Weiner Filtering: Is a type of linear filtering that is applied to an image adaptively thereby tailoring itself to the local image variance

Image Segmentation Techniques

Image segmentation techniques have been classified into four (4) categories by Abirami and Sheela (2014) and Krishna and Akansha (2010). Every segmentation technique lies under any of these categories. Figure 2.1 shows the hierarchical taxonomy of fundamental segmentation techniques identified by different researchers. The categories identified are:

i. Pixel-Based: Is the simplest approach used for segmentation, in the technique each pixel is segmented based on grey-level values, no contextual information only histogram. Even with perfect illumination, pixel-based segmentation results in a bias of the size of segmented objects when the objects show variation in their grey values. This is as a result that the grey values at the edge of an object change gradually from the background to the object value whereby making darker object to become too small and brighter object to become too large.
ii. Region-Based: Involves selecting initial seed points and adding neighboring pixels to the region depending on the homogeneity criteria. This process is continued until all pixels belong to some region. Thus, region-based segmentation algorithms operate iteratively by grouping together pixels which are neighbours and have similar values and splitting groups of pixels which are dissimilar m value. To improve result of the region-based, feature computation and segment can be repeated until the procedure converges into a stable result.
iii. Edge-Based: Edge-based method attempts to solve the image segmentation by detecting the edge between different regions. This technique determines the presence of an edge or line in an image and outlines them in an appropriate way. The main purpose of edge detection is to simplify the image data in order to minimize the amount of data to be processed. Generally, an edge is defined as the boundary pixels that connect two separate regions. The detection operation begins with the examination of the local discontinuity at each pixel element in an image. This approach can be used to avoid a bias in size of the segmented object without using a complex threshold scheme.
iv. Model-Based: All previous segmentation techniques discussed used only local information, but when the information that can be gathered from local neighbourhood operation is not sufficient to perform the task, a specific knowledge about the geometrical shape of the object is required which can then be compared with local information. Deformable models are curves or surfaces, for segmentation in the image domain, or hyper-surfaces, for the segmentation of higher dimensional image data, such as stacks of images, which

deform under the influence of internal and external forces to delineate object boundary. The internal forces are defined such that they preserve the shape smoothness of the model, while the external forces are defined by the image features to drive the model toward the desired position.

v. Statistical Approach: This approach is based on a statistical modeling of images that consists of a measurement model and a prior model. Each anatomical structure is associated with a class of which is a calculated statistical characteristic. In this context, each case is considered as the result of a stochastic process and is associated with a set of a random variable. The main problem is the estimation of the probability densities measurement model from observations and that the decision knowing these densities as prior models. For estimating probabilities, the most used algorithm is expectation- minimization (EM) or maximum a posteriori (MAP) and for measurement model is supposed that each region of image is associated with a specific distribution and then the probability density of the image is a mixture of probability densities. In general, the Gaussian mixture is considered. The prior model takes into account smoothness and piecewise contiguous nature of the tissue regions and is modeled by a 3-D Markov random field (MRF) which is robust to noise.

Basic Properties of Image Segmentation

Segmentation algorithms are based on two basic properties Salem et al (2010) which are similarity concept and discontinuity concept. Abirami and Sheela (2014) also agreed to this but added the third concept which is Statistical Approach. It is explained as follows:

i. Similarity Concept: Is based on partitioning an image into regions that are similar according to predefined criteria.
ii. Discontinuity Concept: Is to partition an image based on abrupt changes in intensity, such as edges in image.

Image Segmentation Approaches

Various image segmentation approaches have been proposed and the approaches are as follows;

i. Threshold Approach: Is one of the simplest segmentation methods, the pixels are partitioned depending on their intensity levels. Figure 2 shows the different techniques of threshold approach. The method is based on a threshold value which will convert grey scale image into a binary format. Pritee (2012) and Salem et al (2010) grouped the approaches into three (3) different classes which are:
ii. Local Technique morphology: Are techniques that are based on the local properties of the pixels and their neighborhood.
iii. Global Technique: This segment an image on the basis of information obtained globally.
iv. Split, Merge and Growing Technique: Uses both the notions of homogeneity and geometrical proximity in order to obtain good segmentation result.

When a threshold value of an image is selected without human intervention, it is called an automatic threshold scheme. This can be achieved through the knowledge of the intensity characteristics of the objects, fraction of the image occupied by the objects and the number of different types of objects appearing in the image.

Threshold value can be applied as:

$$T = T\ \{x,y,p\ (x,y),\ f\ (x,y) \qquad (1)$$

T — is the threshold value

X and y are the coordinates of the threshold point

p(x,y) and f(x,y) are points of the gray level image pixels.

i. Watershed Approach: This is a segmentation technique that uses image morphology, the watershed technique is based on a topological interpretation of the image. The intensity levels represent the height of the terrain that describes mountains and basins Pritee and Vandana (2012). Good results of watershed entirely depend on the image contrast, badly contrast images can cause the approach to generate' over segmentation. The watershed algorithm is applied to the gradient of the image to be segmented. Acharjya et al (2013) recognized watershed approach as a powerful method used in image segmentation due to its many advantages such as simplicity, speed and complete division of the image.
ii. Clustering: Clustering techniques are used for mining data to discover useful patterns. According to Rupanka and Samarjeet (2014), clustering methods produce distinctively different groups out of data objects from a given data set. Each of these groups contains object which are similar to other objects in the same group and are dissimilar to objects in other groups. Abirami and Sheela (2014) classified clustering algorithm as exclusive clustering (e.g. K-means) and overlapping clustering (e. g. Fuzzy C-means). Advantages of the clustering method are speed and lack of requirement for any training data while the drawbacks are sensitivity to noise and affectability by in homogeneities. Also, spatial modeling is lacking in this method.
iii. K-Means Clustering: K-means clustering approach is an unsupervised method. K means clustering is used because it is simple and has relatively low computational complexity. In addition, it is suitable for biomedical image segmentation as the number of clusters (K) is usually known for images of particular regions of human anatomy.

Problems with Medical Image Segmentation

Segmentation of medical images is a challenging problem due to complexity of the images, absence of models of the anatomy that fully capture the possible deformations in each structure. Medical images require more accuracy than natural images. Automatic segmentation is a difficult task since most images are complex in nature. Neeraj and Aggarwal (2010) identified reasons that affect the results of medical image segmentation algorithms. The reasons mentioned are partial volume effect intensity homogeneity, presence of artifacts and closeness in gray level of different soft tissue. The inherent problems in medical images as identified by
(Rupanka and Samarjeet, 2014) are partial volume effect where a single pixel volume is comprised of a mix of different tissue classes, intensity non uniformity where there is variation in the intensity level of single tissue class and noise which can alter the intensity of a pixel resulting in uncertain classification. Brain tumor diagnosis is quite tedious due to multiple shapes, sizes, location and appearance of tumor in the brain (Vipin et al,.2015). Kapu et al,. (1995) also identifies other inherent problems which are random frequencies (RF) in homogeneity, partial volume effect, noise, insufficient resolution (large, slice, thickness), anatomic variability and complexity, differentiating thin structures while there is existence of noise. There is no universal approach for segmentation of every medical image and each imaging system has its own specific limitations (Neeraj and Aggarwal, 2010). To overcome the shortcoming of segmentation approach, hybrid models are proposed to segment medical images.

Applications of Medical Image Segmentation

It has become almost compulsory to use computers to assist radiological experts in clinical diagnosis, treatment planning. Reliable approaches are required for the delineation of anatomical structures and other regions of interest (ROI) (Neeraj and Aggarwal, 2010). According to Feng and Xianaghua (2013), the improved segmentation results can be used to reconstruct 3D structures of tissues and enhance the real-time visualization on the screen for clinicians to navigate through the data. This can provide great benefits to many applications, including locating tumors, measuring tissue volumes, surgery, and diagnosing diseases.

MATERIALS AND METHODS

Hybrid Segmentation Approach

This is the integrating of two or more technique which is efficiently giving improved outputs compared to the segmentation approach working alone. This is all possible in the field of image processing, predominantly in the area of medical image segmentation. Image segmentation means separating the object from the background. Image segmentation acts as a heart to the classification technique. The major problem in watershed and threshold working in single alone approach is inability to overcome noise, under segmentation in the brain tumor detection. So, this problem is revealed by this hybrid segmentation technique. The expected result can be done by the combined techniques of watershed and threshold segmentation. The performance of this proposed hybrid technique result depends on similarity measure used by the method and its implementation.

Watershed Segmentation Approach

The watershed technique is based on a topological interpretation of the image. The intensity level represents the height of the terrain that describes mountains and basins. The traditional transformation algorithm is usually implemented by simulating a flooding process, the image is taken as a surface of mountainous terrain and the grey value of each pixel denotes the altitude of that point. In this terrain, there exist deep valleys (minima), high ridges, (watershed lines) and steep or gentle hillsides (Catchment Basins). Firstly, holes are pierced in each minimum and then this surface is slowly immersed into a lake, starting from the minima of lowest altitude, water will progressively fill up the different catchment basins. At the point where the water coming from different minima would merge, a 'dam' is built to prevent intermingle. At the end of the flooding procedure, each minimum is completely surrounded by dams which delimit its associated catchment basins. All the dams correspond to the watersheds that are needed. The watershed approach is applied to the gradient of the image to be segmented. Noise and other irrelevant details can lead to over-segmentation in watershed. Over-segmentation is handled by de-noising an image and preserving features such as edges and this is done by applying topological gradient. For a better edge preservation, one has to threshold the topological gradient with a small enough co-efficient.

Threshold Approach

Threshold is a process of converting a gray scale input image to a bi-level image by using an optimal threshold. The purpose of threshold is to extract those pixels from some image which represent an object (either text or other line Image data such as graphs, maps). Though the information is binary the pixels represent a range of intensities. Thus, the objective of binarization is to mark pixels that belong to true foreground regions with a single intensity and background regions with different intensities. For a threshold approach to be really effective, it should preserve logical and semantic content. In global threshold, a single threshold for all the image pixels is used. When the pixel values of the components and that of background are fairly consistent in their respective values over the entire image, global threshold could be used.

The threshold value T is obtained from the gray image and it can be classified into black (0), white (1) where g (x, y) = [1 $if\ f\ x, y > T$ 0 $if\ f\ x, y \leq T$] (2)

Where $f\ x, y$ is an input image, g(x,y) threshold/segmented image, T threshold value.

The process of threshold segmentation is:

i. Initial estimate of threshold T.
ii. Perform segmentation using T (i) P1, pixels brighter than T (ii) P2, pixels darker than T.
iii. Apply average intensities m1 and m2 of P1 and P2.
iv. Compute new threshold value Tnew = $\boldsymbol{m1}+\boldsymbol{m2}/\ \boldsymbol{2}$
v. If │T - Tnew│>ΔT, repeat step 2. Otherwise stop the process. where m1 and m2 are mean of intensities, P1 and P2 is a probability of brighter and darker pixels and T and Tnew are the thresholds.

MRI brain image explicitly contains tumor portion and is taken as an input image. This work contains three steps.

Step 1: The pre-processing steps (i.e. gray scale conversion, contrast enhancement) have done.

Step 2: The results of single seed region growing and threshold segmentation results are multiplied.

Step 3: Performance of the existing system can be measured by the various quality metrics.

Flow Diagram

This is the flow diagram that shows the overall process involved in the existing system

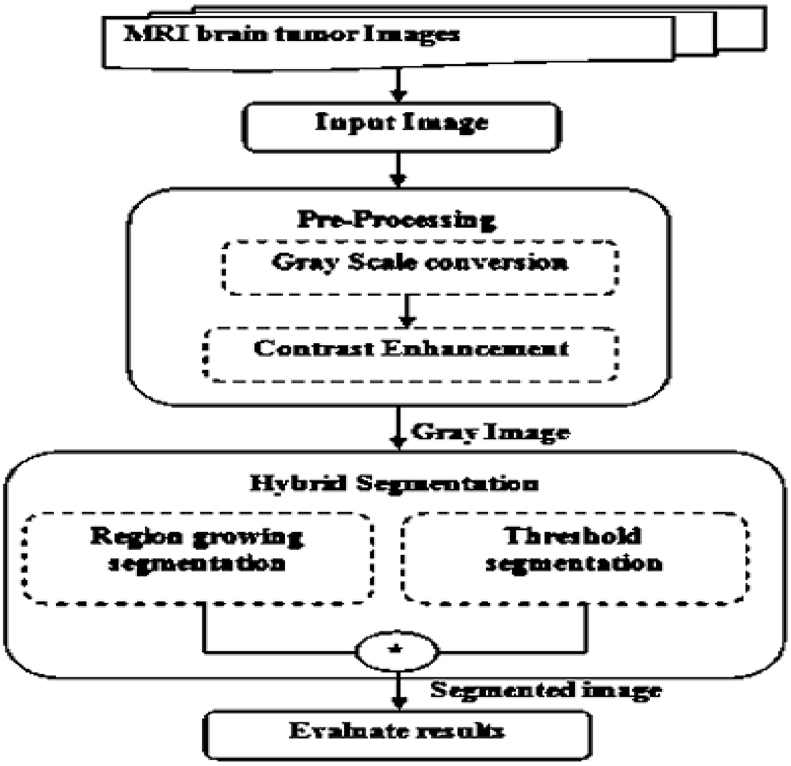


Figure 1: The flow diagram of overall process of the existing system (Anithadevi and Perumal, 2015)

Threshold

The input image was converted to grayscale image using the MAT LAB in built functions. The function eliminates the hue and saturation information while retaining the luminance for intensity.

dst (a, b) = {maxVal. if img(a, b) >1, 0 otherwise}

Binarize image = grayscale image >T

bij = 1 for aij> T

bij= 0 for aij<T

Watershed

Distance transform takes the complement of binary image as an input. The concept of the distance transform is the distance from every pixel to its nearest zero valued pixel. Each single valued pixel has a distance transform value of 0 as it is the closest non zero valued pixel of itself. The Complement of the distance transform is taken and it force pixels that do not belong to the objects to be at Inf. The background marker was computed by labeling the region which is sure of being the foreground

General Overview of the Proposed Model

Figure 2 depicts the overview of the proposed model while the work flow of the same proposed model is shown in Figure 3

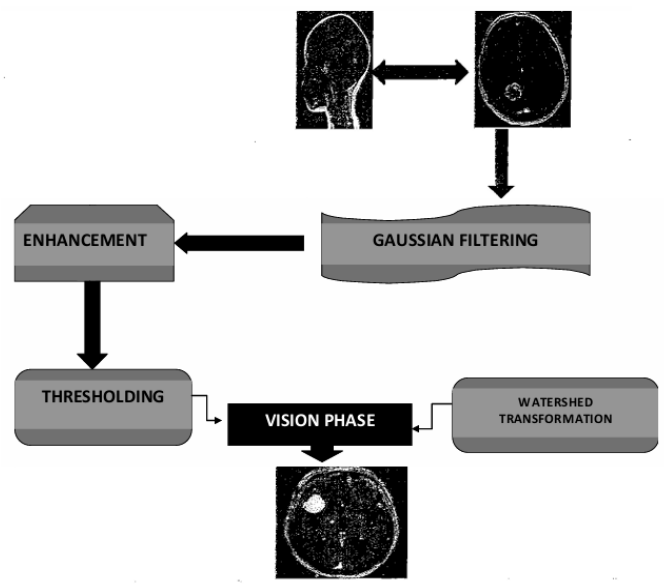


Figure 2: Overview of the Hybrid Framework

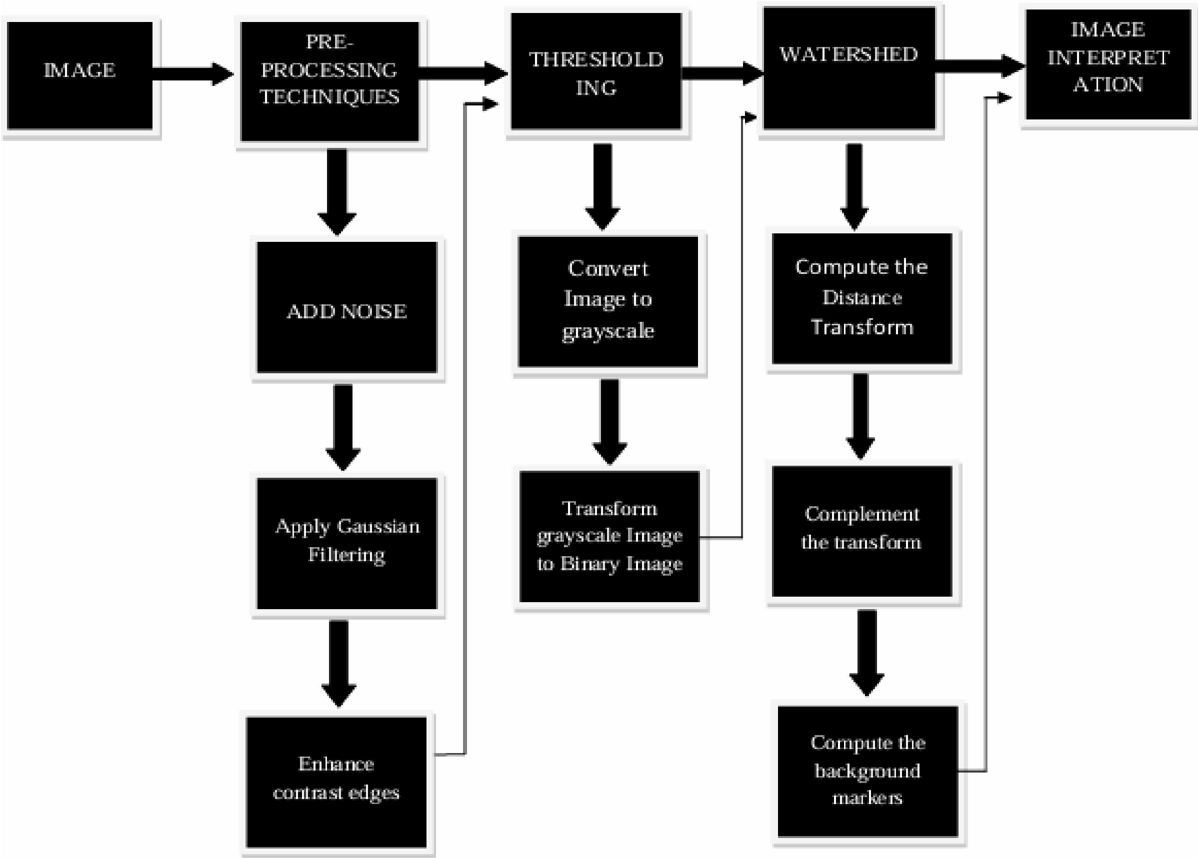
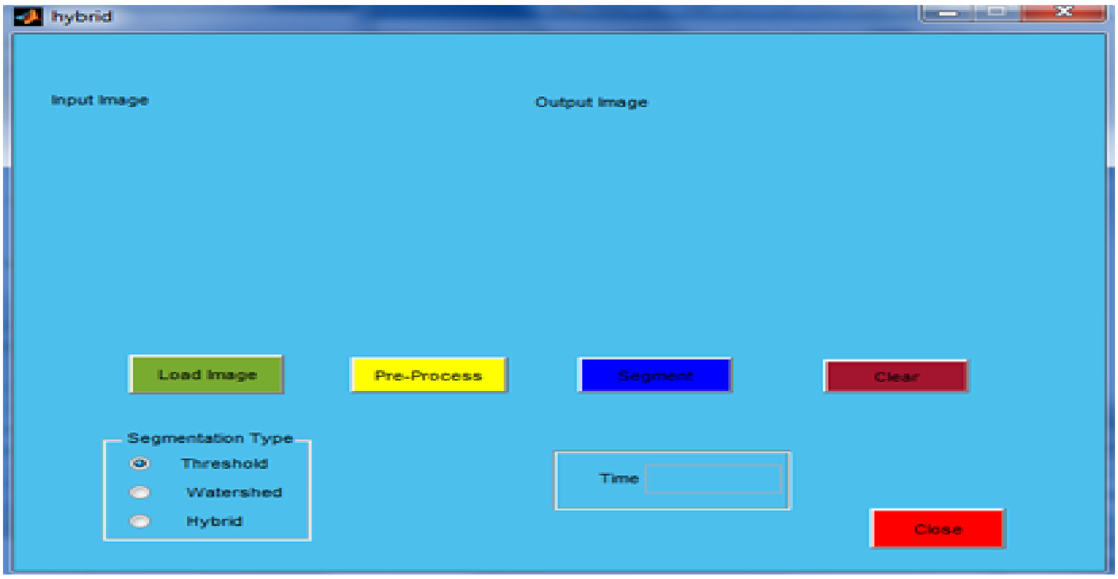


Figure 3: Work flow diagram for the interoperability of Watershed and Threshold for Hybrid Segmentation

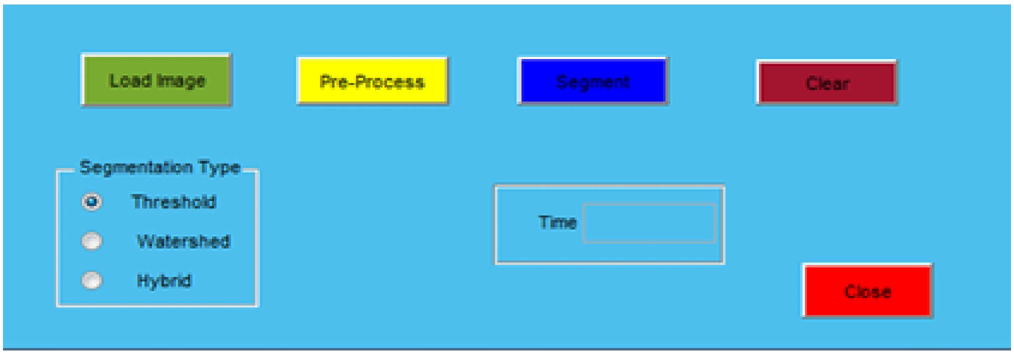
System Design and Implementation

System Interfaces

This shows the hybrid framework interface which comprises input image board displays loaded images, output image-board, display of segmented image, load image button, reprocess button, segmentation button, clear button, segmentation type, time and close button.



(a) Main menu



(b) Submenus

Figure 4: Interfaces of the Hybrid Segmentation Framework

Algorithm

Step 1: Obtain MRI scan images in a two-dimensional metrics.

Step 2: Store the MRI scans in database of images in JPEG image formats.

Step 3: Pre-process the MRI scan

i. Remove noise by applying Gaussian filtering
ii. Enhance contrast edges

Step 4: Threshold the contrast edges images

i. Convert the image to gray scale
ii. Transform the gray scale uses to binary image

Step 5: Watershed the binary image

i. Compute the distance transform of the binary images
ii. Complement the transform
iii. Compute the background markers

RESULTS AND DISCUSSION

Datasets containing MRI brain images were obtained from Virtual skeleton database of the SICAS medical image repository. The obtained and scan images were displayed in a two-dimensional matrix having pixel as its element. Images were stored in MatLab directories and displayed. The entries of the images ranged from 0-1 where 0 shows to black color and 1 show pure white color. Entries between this ranges varies intensity from black to white. For experimental purposes datasets of 40 patients were used to test and train the hybrid segmentation framework. The hybrid segmentation framework used the same performance measures in the performance evaluation as proposed in the work of Anithadevi and Perumal (2014) which is accuracy, precision, sensitivity, recall, f-measure and g-mean of ground truth images and segmented images.

Performance Evaluation Parameters

Accuracy

Accuracy regards to systematic errors; the accuracy is directly proposed to the results consider both true positives and true negatives among the total number of cases scrutinized. To make the context clear by the semantics, it is frequently defined as the "rand accuracy". It is a parameter of the test.

Accuracy = (no of TP+ no of TN) / (no of TP +FP +FN +TN).

Precision

Precision is related to random errors; it is referred as the direct proportion of the true positives against all the result of positives (both true positives and false positives). The high precision means that an algorithm returned substantially more appropriate results than irrelevant. Precision is used to measure the specificity and it reaches its best value at 1 or nearest to 1.

Precision = (no of TP) / (no of TP + FP)

Recall

High recall means that an algorithm returned most of the pertinent result. Recall is used to measure sensitivity and it reaches its best value at 1 or nearest to 1.

Recall = TP / (TP+FN)

F Measure

In statistical analysis of binary segmentation, the Fl score (also F-score or F-measure) is a measure of a test's accuracy. The Fl score can be construed as a weighted average of the precision and recall, whereas an Fl score reaches its best value at 1 or nearer to 1 and worst value at 0 or nearer to 0. It can be defined as

F=2*((precision*recall)/(precision+recall))

G Measure

It is the geometric mean of Recall and Precision and it can be defined as $G = \sqrt{precision. Recall}$

False Alarm Rate

Recall False Alarm Rate is the number of false positives that are expected to occur in a given number of face-sized segments, or in a given entire image, taken from a given scene. It reaches its best value at 0 or nearer to 0 and worst value at I or nearer to 1.1t is calculated as:

False Alarm Rate=FP / (FP+TN)

Table 1: Condition for Ground Truth Image

	Tumor Present	**Tumor Absent**
Tumor	TP	FP
Non-Tumor	FN	TN

Table 1 shows the parameter used in the achievement of the result as condition ground truth image.

Table 2: Output Value for Threshold Approach

	Tumor Present	Tumor Absent
Tumor	22	4
Non-Tumor	4	8

Table 2 shows the outcome of segmented images when threshold approach was used.

Table 3: Output Value for Watershed Approach

	Tumor Present	Tumor Absent
Tumor	23	4
Non-Tumor	5	8

Table 3 shows the outcome of segmented images by watershed approach.

Table 4: Output Value for Hybrid Framework

	Tumor Present	Tumor Absent
Tumor	24	3
Non-Tumor	4	9

Table 4 shows the outcome of the segmented images when hybrid framework was applied.

Results of the Proposed Hybrid Framework

The table below shows the results gotten when the condition for the ground truth images were calculated using the performance evaluation measures as stated above

Table 5: Results of performance evaluation

	Threshold	Watershed	Hybrid
Accuracy	0.7895	0.7750	0.8250
Precision	0.8462	0.8519	0.8889
Recall	0.8462	0.8214	0.8571
F-Measure	0.8462	0.8365	0.8729
G-Measure	0.8462	0.8365	0.8729
False Alarm Rate	0.3333	0.3333	0.2500

Table 6: Performance Analysis of Previous Work Done in Hybrid Segmentation Techniques

Methods	Images	Accuracy	Precision	Recall	F-measure	G-measure
Region Growing	Image 1	0.7342	0.6745	0.7112	0.6996	0.8345
	Image 2	0.6978	0.7342	0.7654	0.7908	0.7890
	Image 3	0.7779	0.8654	0.8543	0.7809	0.8100
	Image 4	0.8090	0.7000	0.8117	0.8099	0.8587
Threshold	Image 1	0.7250	0.7476	0.8990	0.8000	0.9180
	Image 2	0.8527	0.7905	0.9078	0.7090	0.8999
	Image 3	0.8123	0.8125	0.7888	0.8609	0.8678
	Image 4	0.8234	0.8800	0.8101	0.9000	0.8911
Hybrid	Image 1	0.9249	0.9777	0.9034	0.9927	0.8769
	Image 2	0.9781	0.9342	0.9456	0.9314	0.9235
	Image 3	0.9502	0.9523	0.8210	0.8999	0.9156
	Image 4	0.9827	0.9860	0.9987	0.9797	0.9843

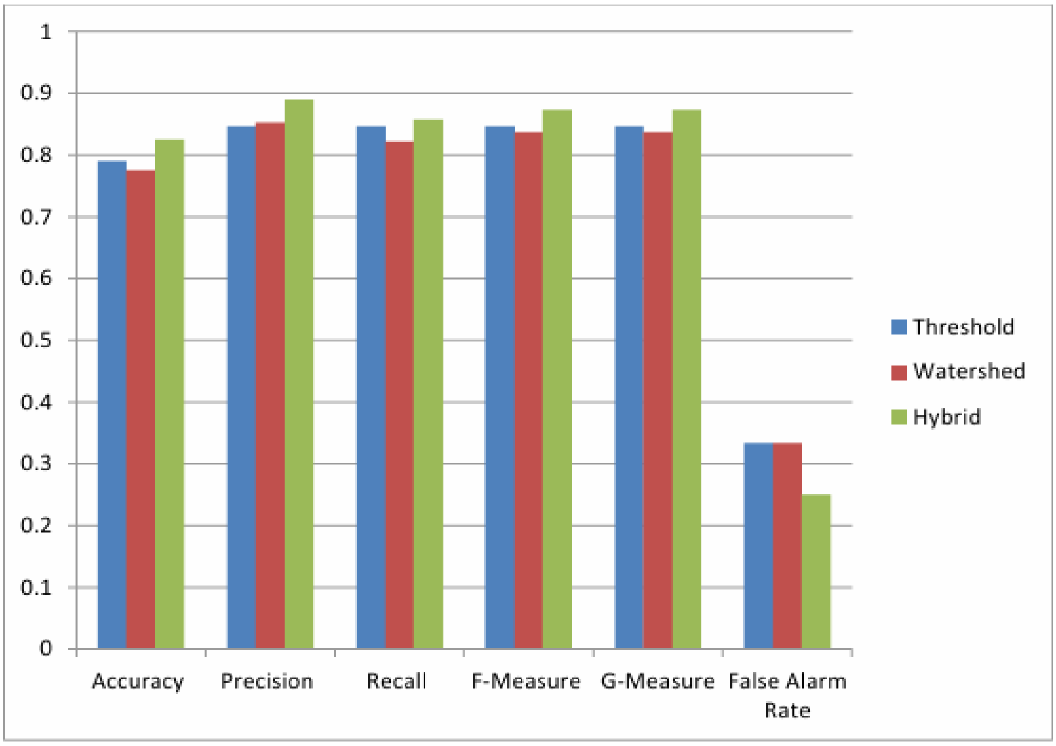


Figure 5: Performance Evaluation Graph of the Proposed Hybrid

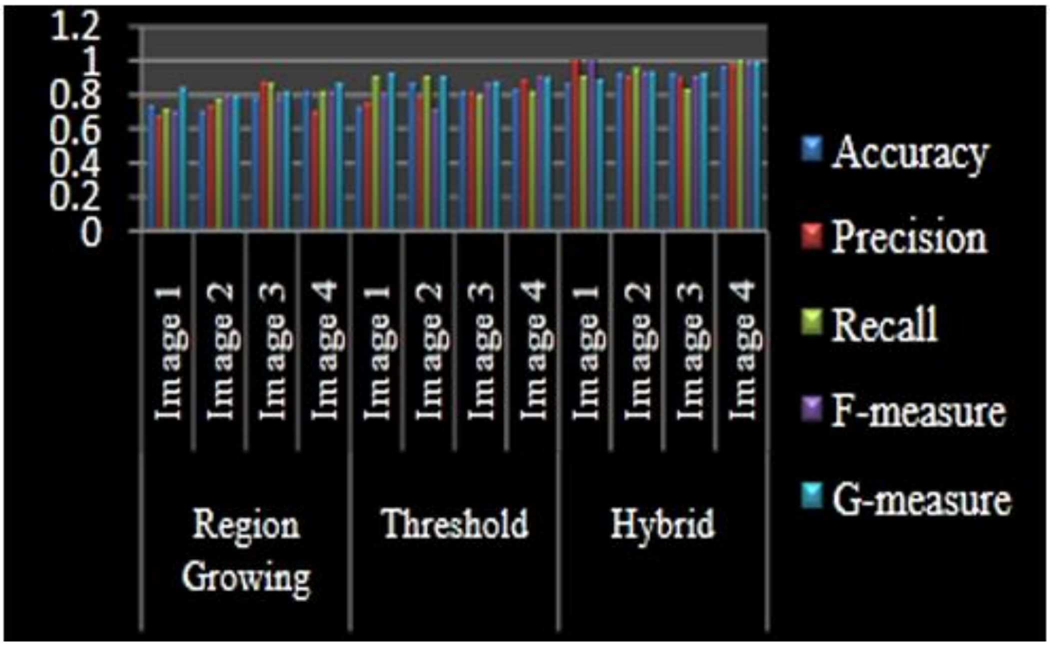


Figure 6: Performance Evaluation Graph of the Previous Hybrid

Image segmentation is typically used to locate objects and boundaries in image. Low contrast edges and noise in images always affect the output of segmented images. There are various techniques of segmentation but each technique has it drawback, when it comes to medical image no single technique has been able to effectively segment medical image. Hence there is a need for hybrid segmentation. Hybrid segmentation had reduced drawback of watershed and threshold approaches in order to produce an efficient framework. Various research works has been carried out on brain tumor segmentation and the most effective are those research works on hybrid segmentation of medical images. Hybrid segmentation framework was tested with 40 datasets of brain images and the framework was evaluated based on performance measure techniques which compared the ground truth image condition with the output of the hybrid framework.

CONCLUSION

Hybrid image segmentation framework is said to be effective and efficient when it was compared to watershed and threshold approaches individually, and as result outperformed in Accuracy, Precision, Recall, G Measure, F Measure values that are nearer to 1 than the other approaches individually.

RECOMMENDATIONS

i. Application Areas: The hybrid image segmentation system can be applied as a diagnostic system for brain tumor detection whether as benign or malignant, lung cancer, fibroid, breast cancer.
ii. Suggestion for Further Research: Further research can be done as regards to color image segmentation and also 3Dreconstruction of the image with quantum computing.

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