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IMAGE PROCESSING TECHNIQUE FOR BRAIN ABNORMALITY DETECTION

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ABSTRACT
The proposed method is to segment the brain tumor. It comprises of pre-processing we can use filtering to remove noise and morphological operation to segments normal tissues by considering spatial information. The process is also intended to segment the tumor cells as well as the removal of background noises for smoothening the region, results in presenting segmented tissues and parameter evaluation to produce the algorithm efficiency. Grey level co-occurrence matrix is employed to convert feature extraction. K-nearest neighbour to classify the conventional and abnormal tissue. When classification of traditional and abnormal tissue to find. Finally we measure the performance.
INDEX TERMS – *Support vector machine algorithm (SVM), K-nearest neighbour.*

1. INTRODUCTION

Tumor image processing involves three stages namely pre-processing, segmentation and morphological operation. The proposed methodology is helpful in generating the reports automatically in less span of time and advancement has resulted in extracting many inferior parameters of the tumor. The same process going to apply the signal processing, here we are getting features values to check the EEG signal. In this approach to finding the signal is normal or abnormal condition. Finally we are getting result from both image and signal features and also to improve the better performance value.An image is a two-dimensional picture, which has a similar appearance to some subject usually a physical object or a person.Image is a two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue. They may be captured by optical devices—such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural objects and phenomena, such as the human eye or water surfaces.The word image is also used in the broader sense of any two-dimensional figure such as a map, a graph, a pie chart, or an abstract painting. In this wider sense, images can also be rendered manually, such as by drawing, painting, carving, rendered automatically by printing or computer graphics technology, or developed by a combination of methods, especially in a pseudo-photograph.

An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. However different computer monitors may use different sized pixels. The pixels that constitute an image are ordered as a grid (columns and rows); each pixel consists of numbers representing magnitudes of brightness and color. Each pixel has a color. The color is a 32-bit integer. The first eight bits determine the redness of the pixel, the next eight bits the greenness, the next eight bits the blueness, and the remaining eight bits the transparency of the pixel.

Image file size is expressed as the number of bytes that increases with the number of pixels composing an image, and the color depth of the pixels. The greater the number of rows and columns, the greater the image resolution, and the larger the file. Also, each pixel of an image increases in size when its color depth increases, an 8-bit pixel (1 byte) stores 256 colors, a 24-bit pixel (3 bytes) stores 16 million colors, the latter known as true color.

Image compression uses algorithms to decrease the size of a file. High resolution cameras produce large image files, ranging from hundreds of kilobytes to megabytes, per the camera's resolution and the image-storage format capacity. High resolution digital cameras record 12 megapixel (1MP = 1,000,000 pixels / 1 million) images, or more, in true color. For example, an image recorded by a 12 MP camera; since each pixel uses 3 bytes to record true color, the uncompressed image would occupy 36,000,000 bytes of memory, a great amount of digital storage for one image, given that cameras must record and store many images to be practical. Faced with large file sizes, both within the camera and a storage disc, image file formats were developed to store such large images.

2. LITERATURE SURVEY

Various strategies have been adopted to handle the problem of high false alarm rate due to the noises and artifacts [1]-[6]: (i) ECG denoising based approach to suppress the noises and artifacts in the ECG recordings and (ii) signal quality indices (SQI) based approach to assess the clinical acceptability of the recorded ECG signals.

ECG Denoising Based Strategy: To reduce the false alarm rates, various ECG denoising methods have been presented based on the moving average and median fil-ters, frequency-selective filters, adaptive filters, Wiener fil-ters, polynomial filters, singular value decomposition (SVD), discrete cosine transform (DCT), discrete wavelet transform (DWT), switching Kalman filters, empirical mode decompo-sition (EMD), nonlinear Bayesian filter (NBF), mathematical morphological (MM) operators, principal component analy-sis (PCA), independent component analysis (ICA), nonlo-cal means (NLM) method, variational mode decomposition (VMD), and EMD-wavelet method for removal of single and combined ECG noise sources. Most existing de-noising methods are highly capable of suppressing noises and artifacts that are very different from those of ECG morphology. Evaluation results show that the baseline wander removal methods may distort the ST-segment due to the attenuation of the low-frequency components of ECG signal[7]. Results further show that simple filters are not adequate to remove severe EMG noise without distorting the amplitude, duration, interval and shape features of the ECG signal . The EMD based denoising method introduces significant distortion at the beginning and end of QRS complexes that may cause widening of the QRS complex . Thus, the denoising methods signif-icantly alter the ECG local waves due to the impossibility of handling the problem of ECG noises and artifacts that considerably overlap with spectrum of ECG signals, in the range of 0.5 Hz to 100 Hz.

Signal Quality Assessment Based Strategy: Besides the noise reduction strategy, signal quality assessment (SQA) strategy has been employed to tackle the false alarm problem. Most methods were presented for classifying the recorded ECG signals into acceptable or unacceptable[5]-[7]. This section briefly describes the feature extraction for assessing the ECG signal quality. D. Tobon Vallejo et al. proposed a modulation spectrum-based ECG quality index based on the spectral signal representation and correlation. C. Orphanidou et al. proposed signal quality indices based on the heart rates, RR interval features and template matching. E. Morgado, et al. proposed an ECG quality estimation method based on the cross-correlation among leads, decision-tree and SVM classifier. J. Behar et al. investigated the ECG signal quality using seven SQIs, such as the kurtosis SQI (kSQI), the skewness SQI (sSQI), the relative power in the QRS complex (pSQI), the relative power in the baseline (basSQI), the fraction of beats detected by wqrs that matched with beats detected by eplimited (bSQI), the ratio of the number of beats detected by eplimited and wqrs (rSQI), and the ratio comprising of the sum of the eigenvalues associated with the five principal com-ponents over the sum of all eigenvalues obtained by principal component analysis of the time-aligned ECG cycles (pcaSQI), and the SVM classifier. P. X. Quesnel et al. proposed an ECG signal quality analysis based on the ensemble averaging of detected PQRST complexes and average PQRST complex subtraction from each of the PQRST complexes of ECG signal. G. D. Clifford et al. investigated seven signal quality indices (iSQI, bSQI, fSQI, sSQI, kSQI, pSQI, and basSQI) with multi-layer perceptron (MLP) and SVM classifiers for determining clinical acceptability of ECG signals. L. Johannesen and L. Galeotti proposed an automatic ECG quality scoring methodology based on the QRS feature extraction and rule-set. Li et al. performed ECG signal quality assessment based on the spectral distribution signal quality index (sdSQI), the comparison of multiple QRS detectors on a single lead (bSQI), the degree of agreement between beat detection on different leads (iSQI), and the kurtosis of the ECG (kSQI). J. Lee et al. presented an automatic motion and noise artifact detection using empirical mode decomposition, three statistical measures such as the Shannon entropy, mean, and variance of the first IMF, and feature thresholding rules. D. Hayn et al. presented a QRS detection based ECG quality assessment using the QRS complex, RR interval time-domain waveform features and the feature thresholding rules.

3. PROPOSED SYSTEM

The projected System deals with enhanced accuracy in classification by enhancing Pre-Processing techniques and Dual-Tree advanced moving ridge transforms it improvement of separate moving ridge rework. Grey level co-occurrence matrix is employed to convert feature extraction. K-nearest neighbour and Neural Network are employed to classify the conventional and abnormal tissue. When classification of traditional and abnormal tissue is send to the spatial fuzzy agglomeration model is employed to calculate quantity of neoplasm cell.

Methodology

Preprocessing-Preprocessing the input image

Image enhancement -by denoising the image using the algorithm called anisoft Filter

Feartures extraction-Extracting the morphological features.

Thresholding-In addition to thresholding the extracting image Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images

Segmentation-Then segmentation process will carried out for further performance to identified the tumor is benign and malignant

SVM-Now the Support Vector Machine(SVM) classifier is used for classification as well as in regression conditionSVM Classifies the tumor is benign or malignant

Algorithm Used for Detection for Tumor:

Step 1: Input the image

Step 2: Convert the RGB image to grey

Step 3: Use the filters for removing noise and perform subtraction operation and form histogramic equivalent for Contrast enhancement.

Step 4: Apply Watershed Segmentation for tumor detection

Step 5: Perform morphological operations for calculating Area, Third moment, Entropy, Mean, Standard Deviation.

Step 6: Tabulate and Compare the parameters calculated for normal and abnormal images.

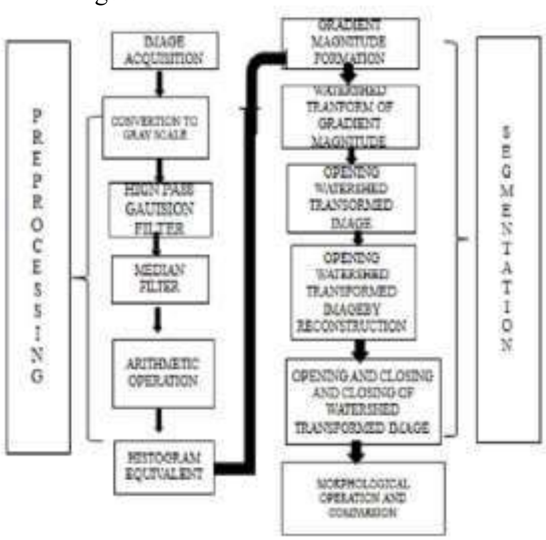

Fig 1:Block Diagram

The source images were obtained from Stanley Medical College under the guidance of Dr. Valarmathi that includes one normal image of one normal CT and MRI and also one Abnormal CT and MRI.

Schematic of the Study

Pre-processing: Image pre-processing aims to improve the image data by suppressing the undesired distortions and enhances some of the image features that will be helpful in further processing. The goal of Pre-processing is to remove the noise and to provide Contrast Enhancement to improve the image quality.

Conversion to Gray Scale: A grayscale image only consists of gray scale values, but MRI images consist of primary colors (RGB) content. A 'Gray' color is one in which the red, green and blue components all have equal intensity in RGB space and so it is only necessary to specify a single intensity value for each pixel, as opposed to the three intensity values needed to be specified for each pixel in a full color image.

Filtering: Filtering is a technique used for eliminating the noise present in an image. The median filter that provides median values of the pixels are used because the mean values obtained using averaging filters results in blurring of the image. In MRI, Gaussian and salt and pepper noise are more predominant. Salt and Pepper noise can be eliminated by median filter, whereas Gaussian noise is eliminated by a Gaussian high pass filter.

Gaussian High Pass Filter: It is done to sharpen the image. A high pass filter preserves the high frequency information within an image while reducing the low frequency information, thus emphasizing the transitions in the image intensities. In high pass filtering, the brightness of the centre pixel is increased relative to its neighboring pixels by the kernel of the filter. The kernel array consists of a single positive value at its centre, which is completely surrounded by negative values. Figure 2 shows the after applied Gaussian HP filter image.

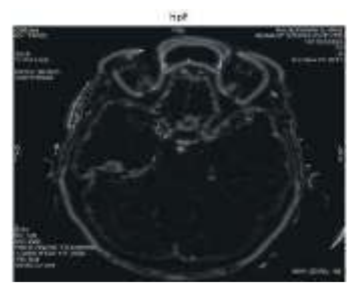

Fig. 2: After applying Gaussian HP filter

Median Filter: The median filter is used to reduce the salt and pepper noise present due to motion artifacts (movement of patient during scan) in the CT/MRI images. It is done for smoothening of CT/ MRI brain image. Here we are using 25x25(CT) and 15x15 (MRI) median filter to eliminate salt and pepper noise.

Image Enhancing by Subtraction: Image enhancement provides the details that are obscured and highlight certain features in an image. The fundamental enhancement needed in the CT/MRI images is the contrast enhancement. In this paper we perform subtraction operation and histogramic equivalent formation for enhancing the contrast of CT/MRI brain image. Subtraction operation is performed on a pixel by pixel basis sequentially, one pixel at a time, or in parallel, where all operations are performed simultaneously.

Forming Histogramic Equivalent: A histogram is a way to graphically represent the distribution of data in a data set and Histogram equalization is a technique for adjusting image intensities to enhance contrast of an image by determining the pixel values. Better contrast is obtained via the histogram of the image, then using histogram equalization that allows the areas with low contrast to gain higher contrast by spreading out the most frequent intensity values from this data one can manipulate an image to meet the required specifications. In order to create a histogram from an image, the mist function is used. Contrast enhancement can be performed by the haste function. At first the gray scale image is taken and its histogram plot is developed as in Figure 3 then by using haste a histogram equivalent for that image is produced as in Figure 4 and its respective plot is shown in Figure 5.

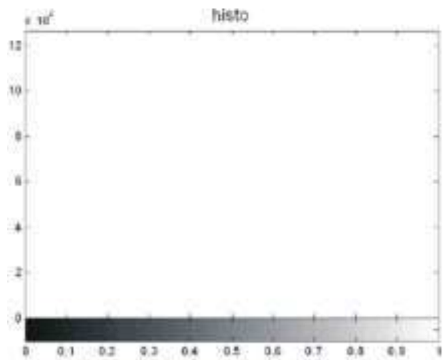

Fig. 3: Histogram plot for subtracted image histogram

Fig. 4: Histogram equivalent

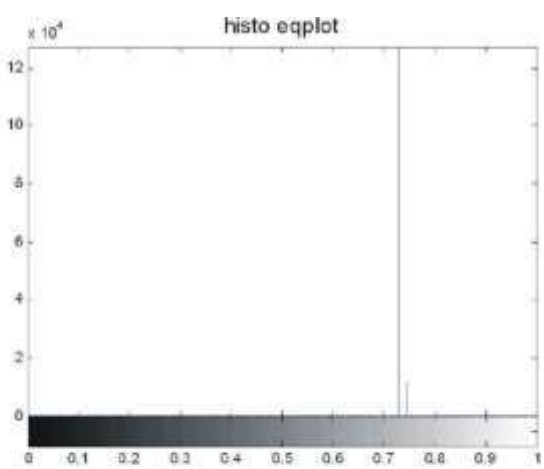

Fig. 5: Histogram equivalent plot for subtracted image (Histogram equivalent plot)

Watershed Segmentation: Image segmentation is stated as the process of assigning a label to every pixel in an image such that Pixels with same label share certain identical visual characteristics. With respect to our paper we are using watershed segmentation. The block diagram of watershed segmentation as shown in Figure 6

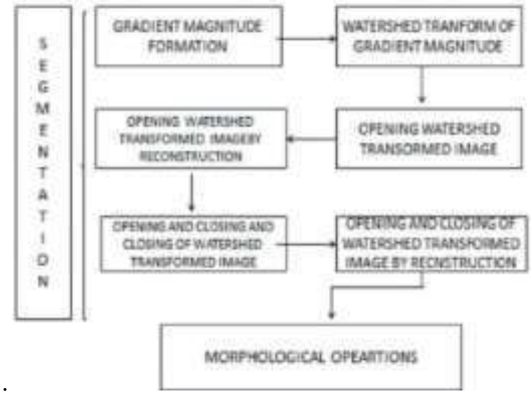

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Fig. 6: Block-diagram for segmentation

Gradient Magnitude Formation: Gradient is termed to be an increase or decrease in the property of an object. By means of using the Sobel edge masks, imfilter and some simple arithmetic the gradient magnitude is formed. The gradient is high at the borders of the objects and low (mostly) inside the objects.

Watershed Transform: The term watershed refers to a ridge that divides areas based on different pixel intensities followed by converting into RGB image with unique labeling based on intensity values.

Marking the Foreground Object: A variety of procedures such as "opening-by-reconstruction" and "closing-by-reconstruction" to "clean" up the image and finally “opening-closing by reconstruction” are performed .

Morphological Operation: Various texture based parameters such as entropy, third moment and intensity based parameters such as mean, standard deviation and finally shape based parameter area of these CT/MR images are extracted and used for further analysis. The parameters are calculated for the segmented images with tumor and without tumor using inbuilt MATLAB functions.

4.RESULTS AND DISCUSSION

Finally the calculated parameters values of abnormal CT and MRI image is compared with the normal CT and MRI image and tabulated the results.

Table 1: Morphological Operation Comparison Ct Image

Parameters	Condition of the Medical Ct Image *Noct (Normal)*	*Ct (Abnormal)*
Mean	100.4136	104.2402
Standard Deviation	55.6128	77.3652
Third Moment	14.2830	12.6429
Area	2407604	2072636
Entropy	0.78640	0.9259

Table 2: Morphological Operation Comparison Mri Image

Parameters	Condition of the Medical Magnetic Resonance Imag *Mri(normal)*	*Mri(abnormal)*
Mean	61.200	75.2044
Standard Deviation	64.4156	75.0729
Third Moment	11.2254	11.2149
Area	373098	410794
Entropy	0.9981	0.9986

5.CONCLUSION

The brain tumor is one in every of the deadliest diseases in today'sworld. In order to find out the cancer tissues at the earliest stage, the proposed system is developed. By analyzing the existing system, the segmentation and classification algorithm are designed by using MATLAB.The Support Vector Machine algorithm provides a solution to detect a brain tumor at an earlier stage. The system imparts an efficient method to identify and segment the tumor from MR image.The brain tumor region is segmented using the extracted features and adaptive SVM classifier helps to identify whether the tumor is benign or malignant. Thus it helps the physician and radiologist for brain tumor diagnosis for human surgery.

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