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Extraction and Features of Tumour from MR brain images

Sai Prasanna M[1], Naga Sai P[2],T.V.C.L. Surekha[3], P. Srikanth[4],V. Sai Swaroop[5]
P.Vasudeva Reddy[6]
[6]*ASST PROFESSOR*
[1 2 3 4 5]*Department of Electronics and Communication*
Bapatla Engineering College

Abstract : *Medical image processing is the most challenging and emerging field now a days. Here we describe the strategy to detect and extraction of Brain tumour from patient's MRI scan Images of the Brain. We collected MR brain images from Harvard Medical School website and OASIS dataset. First Otsu's Binarization is employed and K means clustering for Segmentation. Then wavelet transform and PCA were used to extract and reduce the dimensions of the features. Now from these we calculate the various parameter values.*

Keywords - *Otsu's Binarization, Wavelet Transform, PCA, K-means clustering.*

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I. INTRODUCTION

Brain is the vital part of the human body. Brain tumour is a very serious disease occurs because of uncontrolled growth of cells in the brain. There are different type of tumours occur in the brain, such as benign and malignant. Benign is a non-cancerous tumor, grow slow while malignant tumor is a cancerous tumor, grow fast and causes serious harm to the brain which causes death Magnetic Resonance Imaging (MRI) is an imaging technique that provides high pixel images of the internal structures of the human body, especially in the brain, and provides various information for medical diagnosis and biomedical research. The goal of Image segmentation is to divide an image into its required regions or objects like separation of foreground from background. It is one of the toughest challenges in Image processing and computer vision as it serves as a fundamental step to object recognition, image retrieval, image understanding. A several researches found for image segmentation such as threshold methods, Otsu's method, graph based methods, active contour method, region based methods, edge detection methods, clustering methods, and other hybrid method. A histogram method doesn't work well for images whose histograms are nearly unimodal. Edge based method are not suitable well for complex and noise data as it focus on detecting pixel on the edge of the object. In region growing method over segmentation and under segmentation are critical issues. Graph based methods are high computational complexity. Due to the efficiency and simplicity of Otsu's Method it's mostly used. Here in this paper, for feature extraction Wavelet Transform is employed and for the feature reduction PCA is used. The features like Mean, Standard deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Homogeneity etc will be calculated.

I. METHODS

Our method consists of 3 stages:

1.1 Otsu's Binarization.
1.2 K-means Clustering.
1.3 Wavelet Transform
1.4 PCA
1.5 Calculations.

1.1 Otus's Binarization

This type of segmentation comes under Threshold based Segmentation. For any image, the pixels fall under foreground or background. Here we have to find the threshold value at which the sum of foreground and background spreads is at its minimum. This method is suggested due to its simplicity and effectiveness. Depending on the threshold value the pixels were separated so that their inter class variance is maximum and intra class variance is minimum.

1.2 Clustering

Clustering is an algorithm which divides the image into different number of discrete regions so that the pixels having high similarity will fall in one region and there exist high contrast between each region.
The following are the types of clustering

a. K means Clustering
b. Fuzzy C means Clustering

c. Mountain Clustering
d. Subtractive Clustering

1.2.1 K means Clustering

Here in our methodology K means Clustering was employed because it is computationally faster and work for large number of variables. In this method, the input data is divided into k number of disjoint sets. For each set corresponding centroid value was calculated. Now calculate the distance of each pixel from the centroid. The pixel which is nearest to the centroid will be comes under the corresponding cluster.

1.3 Wavelet Transform

Here in our methodology K means Clustering was employed because it is computationally faster and work for large number of variables. In this method, the input data is divided into k number of disjoint sets. For each set corresponding centroid value was calculated. Now calculate the distance of each pixel from the centroid. The pixel which is nearest to the centroid will be comes under the corresponding cluster.

Gabor adopted a technique to analyze a small section of signal at a time called as Windowing or short time Fourier Transform (STFT) [9]. It gives the information regarding both time and frequency domain. But the drawback of this technique is limitation of size of window.

To overcome this, Wavelet Transform (WT) is employed which is a window technique of variable size. Here both time and frequency information of signal is preserved.

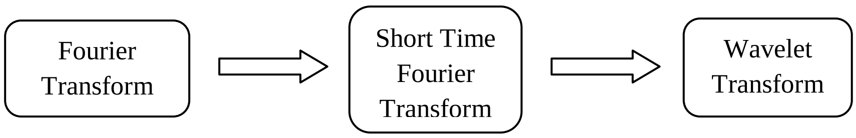

Fig.1: Development of signal analysis

Let x(t) is a square–integrable function, now the wavelet transform of x(t) which is represented as $\psi(t)$ given by

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t)\,\psi_{a,b}(t)\,dt$$

Where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right)$$

Due to its multi-resolution analytic property it allows analysis of images at various levels of resolution. The wavelet $\psi(t)$ is used to calculate $\psi_{a,b}(t)$by performing translation and dilation where a is termed as dilation factor and b is termed as translation parameter. In general there are different types of wavelets transform exists. Harr wavelet is most important and simplest one which is preferred in most of the applications [10-12].

If we consider 2D images, the DWT is applied to every dimension individually. By applying this, at each scale there exist 4 Sub-bands namely LL, LH, HH and HL images. For the next 2D DWT, LL sub-band is used. So the approximation component of image will be sub-band LL and the other sub- bands LH, HL and HH will be taken as detailed components.

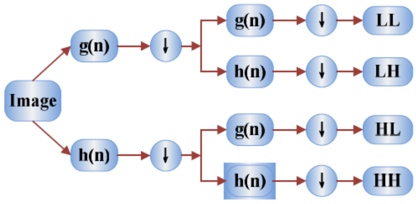

Fig.2: Schematic of 2D DWT

In this paper for the feature extraction level 3 decomposition via Harr wavelet was employed. The schematic for the 3-level wavelet decomposition was shown below.

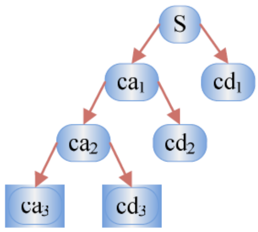

Fig.3: Wavelet decomposition at 3-level

1.4 Principal Component Analysis

This technique requires large storage and is computationally expensive [1], so in order to reduce the feature vector dimensions the principal component analysis (PCA) [2] is used. PCA effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data [3].

The efficient tool to reduce the data set dimension is PCA (Principle Component Analysis) [13]. Here, the data set is transformed to new set of variables in accordance with the variances. Before performing PCA, it is necessary to normalize the input vectors to have zero mean and unity variance. Now for the segmented image various features will be calculated.

1.5 Calculations

We have calculated the various features for the segmented and reduced image. They are

1. Mean which is given as the contribution of every individual pixel in entire image.
   $\mu_x = x_1 p_1 + x_2 p_2 + ... + x_k p_k = \sum x_i p_i$

2. Variance is the measure of how each pixel varies from neighbor pixel.

   Sample variance = $S^2 = \frac{\sum (X-\bar{X})^2}{n-1}$

3. Standard Deviation termed as coefficient of variance.
   $\sigma_x^2 = \sum (x_i - \mu_x)^2 p_i$

4. The Entropy of an image is defined as
   Entropy = $-\sum_i p_i \log_2 p_i$

5. Root Mean Square of an image can be calculated as

   Rms average = $\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$

6. Skewness is given by
   Skewness = $\frac{n}{(n-1)(n-2)} \sum \frac{(x_i - \bar{x})^3}{s^3}$

$$=\frac{n}{s^3(n-1)(n-2)}(S_{above} - S_{below})$$

7. Kurtosis indicates the measurement of luminance changes.
8. Inverse Difference moment measures the texture classification.
9. Contrast indicates the difference in color or brightness.
10. Correlation indicates up to how much extent the members are related.
11. Homogeneity indicates the linearity and equality of the pixels.
12. Smoothness indicates the changing values with the neighbor values and also noise measurement.

II. DATA BASE

Here, the data set contains T2-weighted MR brain images collected from the website of Harvard Medical School and OASIS data set.

The samples of collected MR brain images will be given as follows

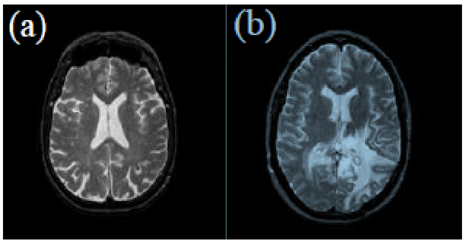

Fig.4: (a) Normal Brain (b) Glioma

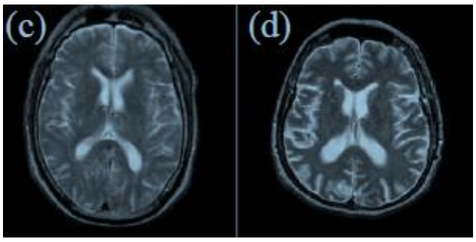

Fig.5: (c) meningioma, (d) Alzheimer's disease

By applying level 3 wavelet decomposition we reduce the input image size which is only 32X32 which is equal to 1024. By applying wavelet transform the features were reduced from 65536 to 1024. But it is too large for calculations. So, PCA is used to reduce the feature dimensions to higher degree.

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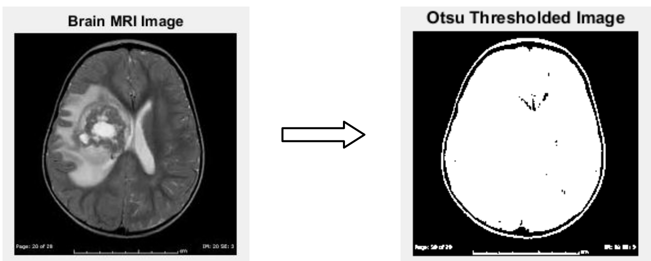

Fig.6: Otsu's Threshold Output

Now for the above input image, segmented output image can be obtained as below:

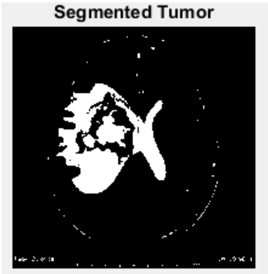

Fig.6: Tumour extracted output

III. CONCLUSION

Finally we extracted the tumour effected region in the brain from MR brain images. We collected two types of tumour effected images benign and malignant. For all the images we have applied the methodologies and also calculated the various feature values like mean, correlation, contrast, variance etc for the segmented image. From these we can analyze the severity of the tumour and can declare the condition of the patient's whether they need further treatment or not.

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