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Analysis of Abnormalities in MRI Images of Brain

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Abstract-

Cancer is currently one of the leading causes of death. This paper presents an approach for detecting not only the detection and early stage of tumours can also detectable. Medical imaging technique is most commonly used to visualize the internal structure and function of the body. Magnetic Resonance Imaging provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does, making it especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging. In recent years the image processing mechanisms are used widely in several medical areas for improving earlier detection and treatment stages, in which the time factor is very important to discover the disease in the patient as possible as fast, especially in various cancer tumours such as the brain cancer, lung cancer, breast cancer. We passed the available brain cancer images and its database in basic three stages to achieve more quality and accuracy in our experimental results : firstly image enhancement stage which we used low pre-processing image techniques: Gabor filter using a Gaussian rule in which produced the best resultant enhanced images. In the image segmentation stage we used thresholding segmentation mechanism by Otsu thresholding algorithm. Finally we relied on general features which help us to make a comparison between normal and abnormal images.

Keywords-Image enhancement, image segmentation, texture analysis, Gabor filter, ostu segmentation, GLCM matrix.

I. INTRODUCTION

In recent years the image processing mechanisms are used widely in several medical areas for improving earlier detection and treatment stages, in which the time factor is very important to discover the disease in the patient as possible as fast, especially in various cancer tumours such as the brain cancer, lung cancer, breast cancer. Both image enhancement and image segmentation are most extraction and recognition have numerous applications on practical approaches among virtually all automated image recognition systems. Feature telecommunication, weather forecasting, environment exploration and medical diagnosis. Image enhancement and image segmentation are

major aspects for most automated image recognition systems. Critical feature extraction and object recognition outcomes result from suitable image processing. Image enhancement is widely used in medical and biological imaging to improve the image quality. The purpose of image enhancement is to enhance weak edges or weak features in an image while keeping strong edges or features. Image enhancement is the converting procedure into the better quality images for feature extraction and object recognition. Image segmentation is about classification of each image pixel to a segment according to the similarity. Segmentation divides an image into its constituent regions or objects. The segmentation of medical images in 2D, slice by slice has many useful applications for the medical professional: visualization and volume estimation of objects of interest, detection of Abnormalities (e.g. tumours, polyps, etc.), tissue quantification and classification, and more. The rest of this paper is organized as follows. In Section 2, we present the image enhancement through gabor filter. In section 3 we present the image segmentation through ostu segmentation. We extract the texture values of images in Section 4 and show experimental results in Section 5. Finally, we make conclusions in Section 6.

II. IMAGE ENHANCEMENT THROUGH GABOR FILTER

The Gabor filter was originally introduced by Dennis Gabor, we used it for 2D images. The Gabor function has been recognized as a very useful tool in computer vision and image processing, especially for texture analysis, due to its optimal localization properties in both spatial and frequency domain. The image presentation based on Gabor function constitutes an excellent local and multi-scale decomposition in terms of logons that are simultaneously (and optimally) localization in space and frequency domains.

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function.

$h(x, y) = s(x, y)g(x, y)$

$s(x, y)$: Complex sinusoid

$g(x, y)$: 2-D Gaussian shaped function, known as envelope

$s(x, y) =$

$$e^{-j2\pi(u_0 x+v_0 y)}$$

$g(x,y) =$

$$\frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)}$$

III. IMAGE SEGMENTATION THROUGH OSTU SEGMENTATION

The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

Thresholding is a non-linear operation that converts a gray-scale image into a binary image where the two levels are assigned to pixels that are below or above the specified threshold value. Suppose that the gray-level histogram corresponds to an image, f(x,y), composed of dark objects in a light background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold 'T' that separates these modes. Then any point (x,y) for which f(x ,y) > T is called an object point, otherwise, the point is called a background point.

Otsu's thresholding technique is based on a discriminant analysis which partitions the image into two classes $C_0$and C_1 at gray level t such that C_0= {0,1, 2,....,t} and C_1= {t+1,t+2,...,L-1} where L is the total number of the gray levels of the image. Let the number of pixels at thei^{th} gray level be n_{th}, and n be the total number of pixels in a given image. The probability of occurrence of gray level i is defined as:

$$p_i = \frac{n_i}{n}$$

$C_0$and C_1 are normally corresponding to the object of interested and the background, the probabilities of the two classes are $w_0$and w_1

$$w_0 = \sum_{i=0}^{t} p_i, \qquad w_1 = \sum_{i=t+1}^{L-1} p_i$$

Thus, the means of the two classes can be computed as:

$$\mu_0(t) = \sum_{i=0}^{t} ip_i / w_0(t)$$

$$\mu_1(t) = \sum_{i=t+1}^{L-1} ip_i / w_1(t)$$

Let σ_B^2 and σ_T^2 be the between-class variance and total variance respectively. An optimal threshold t^* can be obtained by maximizing the between-class variance.

$$t^* = Arg\{\max_{0\le i\le L-1}(\frac{\sigma_B^2}{\sigma_T^2})\}$$

Where, the between-class variance σ_B^2 and total variance σ_T^2 are defined as:

$$\sigma_B^2 = w_0(\mu_0-\mu_T)^2 + w_1(\mu_1-\mu_T)^2$$

$$\sigma_T^2 = \sum_{i=0}^{L-1}(i-\mu_T)^2$$

The total mean of the whole image μ_T is defined as:

$$\mu_T = \sum_{i=0}^{L-1} ip_i$$

An equivalent, but simpler formula for obtaining optimal threshold t^* is as follows:

$$t^* = Arg \max_{0\le t\le L}\{w_0(\mu_0-\mu_T)^2 + w_1(\mu_1-\mu_T)^2\}$$

IV. INFORMATION EXTRACTION USING TEXTURE ANALYSIS

Texture analysis refers to the characterization of regions in an image by their texture content. Texture analysis attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. In this sense, the roughness or bumpiness refers to variations in the intensity values, or gray levels.

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The glcm functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a glcm, and then extracting statistical measures from this matrix. The texture filter functions, described in using texture filter functions, cannot provide information about shape, i.e., the spatial relationships of pixels in an image. To create a GLCM, use the gray co matrix function. The gray co matrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image.

After glcms is created, several statistics are derived from them using the graycoprops function. These statistics provide information about the texture of an image.

The texture features that are considered in the system include:

1. Energy-It measures the number of repeated pairs. The energy is expected to be high if the occurrence of repeated pixel pairs is high. Gray level energy indicates how the gray level component is distributed. The energy measure reaches its maximum value of 1 when an image has a constant value.

$$E = \sum \sum p(i,j)^2$$

p(i,j) is a probability function of an image

2. Entropy- Entropy is the measure of the image information content, which can be interpreted as the average uncertainty of the information source. Discrete entropy is the summation of the products of the probability of outcome multiplied by the log of the inverse of probability of the outcome.

$$H(x) = \sum p(i) \log_2 \frac{1}{p(i)}$$

3. Homogeneity- It means having the property that if each variable is replaced by a constant times that variable the constant can be factored out, having each term of the same degree if all variables are considered as homogeneous.

$$Ho = \sum \sum \frac{p(i,j)}{1+(i-j)^2}$$

The reason for choosing these features is to facilitate the extraction of the most prominent texture features at various resolution, which is essential in the progressive feature extraction algorithm.

V. RESULT

We take five abnormal image and one normal image and find its textures through image processing and then compare the results.

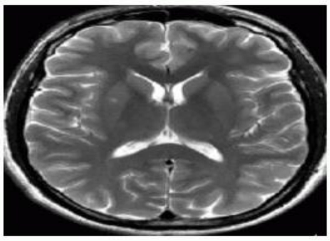

Fig. 1 original image

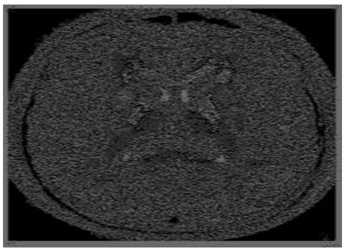

Fig.2 Enhanced by gabor filter

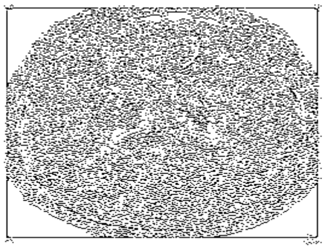

Fig.3 Segmented by ostu segmentation

Table 4.1: Texture features of abnormal and normal image

Image type	Energy	Entropy	Homogeneity
Normal	**0.7209**	**0.4426**	**0.8881**
Abnormal	0.7560	0.3926	0.9038
Abnormal	0.7637	0.3920	0.9093
Abnormal	0.7638	0.3934	0.9102
Abnormal	0.7728	0.3756	0.9109
Abnormal	0.7618	0.3897	0.9061

Table

Features	Mean	Max.	Min.	Normal
Energy	0.76362	0.7728	0.756	0.7209
Entropy	0.38866	0.3934	0.3756	0.4426
Homogeneity	0.90806	0.9109	0.9038	0.8886

4.2: Determination of the range of energy, entropy and homogeneity for abnormal cases

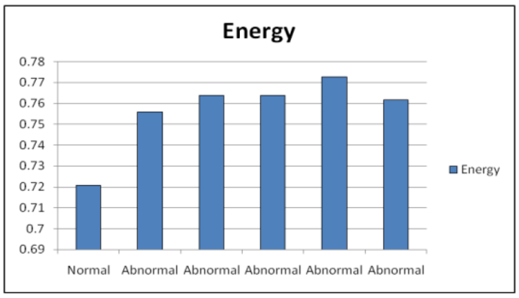

Fig 4 comparison between the energy of normal and abnormal image

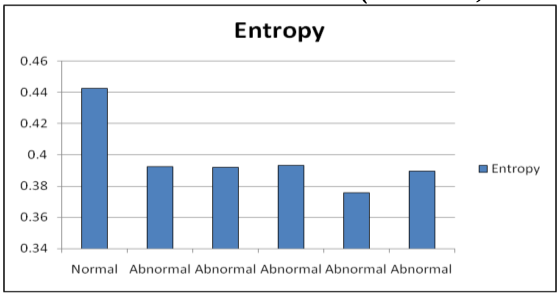

Fig 5 comparison between the entropy of normal and abnormal image

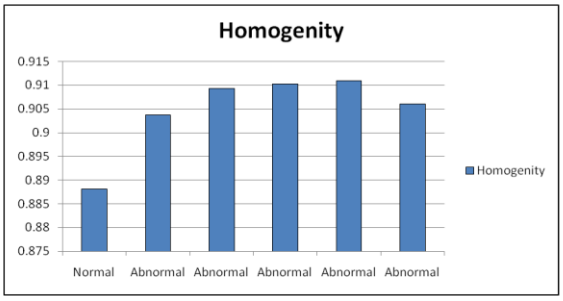

Fig 6 comparison between the homogenity of normal and abnormal image

VI. CONCLUSION

The energy of the normal image is having the least value i.e. 0.7209 and is not within the range of the abnormal images. The entropy of the normal image is having the maximum value i.e. 0.4426 and is not within the range of the abnormal images. The homogeneity of the normal image is having the least value i.e. 0.8881 and is not within the range of the abnormal images.

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