EUROPEAN JOURNAL OF BIOMEDICAL AND PHARMACEUTICAL SCIENCES
http://www.ejbps.com

ISSN 2349-8870
Volume: 3
Issue: 12
523-527
Year: 2016

EARLY DETECTION OF ALZHEIMER'S DISEASE USING HYBRID SEGMENTATION TECHNIQUE AND TEXTURAL ANALYSIS FROM MRI IMAGES

[1]Asmita Ray, [2]Debnath Bhattacharyya and [1]Prof. Samir Kumar Bandyopadhyay*

[1]Research Scholar, Department of Computer Science & Engineering, University of Calcutta, 92 A.P.C. Road, Kolkata – 700009, India.
[2]Department of Computer Science and Engineering, Vignan's Institute of Information Technology, Visakhapatnam-530049, AP, India.

Corresponding Author: Prof. Samir Kumar Bandyopadhyay
Research Scholar, Department of Computer Science & Engineering, University of Calcutta, 92 A.P.C. Road, Kolkata – 700009, India.

Article Received on 20/10/2016 **Article Revised on 10/11/2016** **Article Accepted on 30/11/2016**

ABSTRACT
Alzheimer's disease (AD) is the most common form of dementia, early detection is the most essential step for providing the quality of treatment as life span can be increased and eventually brain research can be benefited with monitoring its effectiveness. Magnetic Resonance Imaging (MRI) technique is mostly used as the diagnosis tool of Alzheimer's disease. A new approach has been developed in this paper for earlier diagnosis of Alzheimer's disease from MRI. The proposed method is carried out in three phases. They are pre-processing, segmentation and feature extraction. In the first phase noise and artifacts have been removed. In the second phase, region affected by the Alzhaimer disease is segmented. In the third phase, affected portion is characterized by the Gray Level Co-occurrance Matrix (GLCM). This paper presents a framework of self- constructed algorithm for detection of AD at an early stage.

KEYWORDS: Alzheimer's disease, Dementia, Magnetic resonance imaging, Gray level co-occurrence matrix (GLCM).

I. INTRODUCTION
Alzheimer's disease (AD) is a neurodegenerative disease, presently worldwide considering the leading cause of dementia that affects mostly elderly people. It is one of the reasons of death in developed country. Early detection plays a key role in delay progression of this disease.

AD is caused by the nerve cells which are losing their ability to function and eventually die due to loss of tissue in the brain.[1] Frontal lobe is first affected by this disease and then gradually spreads to other part of the brain. Alzheimer tissue contains fewer nerve cells and synapses compared to healthy brain.

Alzheimer's disease tends to develops in the area of the brain and gradually get worse over time. There are mainly three stages of AD: (a) Preclinical, (b) Mild Cognitive Impairment (MCI) and (c) Mild Dementia.[2]

Early stage of AD is stated as preclinical. Any kind of symptom has not been noticed during this stage. In MCI, mild changes in memory and in thinking ability have been observed. People with MCI are incapable to judge the amount of time to finish a particular job and may also have trouble to make sound decisions. Severity of the disease is addressed in the mild Dementia stage. In this stage the loss of memory and significant trouble in thinking capabilities, impact on daily functioning Alzheimer's disease is often diagnosed in the mild dementia stage. The major indication of AD is the gradual cognitive declines that mainly begins with gradual loss memory and then proceed to deterioration of thinking capabilities, behavioral changes reflecting the daily life activities as a whole.[3]

The two major abnormalities have been reported in the brain of people with AD: (a) Neurofibrillary Tangles which are made up by the abnormal deposition of protein called tau. (b) Senile plaques which are made from abnormal cluster of protein called beta amyloid. Deposition of tangles and plaque discontinue the function of healthy neurons and finally die with losing connection with other neurons.

AD is the third leading cause of death after heart disease and cancer. It is estimated that worldwide nearly 44 million people have AD and dementia, 5.2 million people of aged 65 and more have Alzheimer's,[4] and approximately 200,000 People, under age 65 have younger-onset Alzheimer's.[5] It is expected that, due to the rapid growth of this popular dementia 1 in 85 people will be affected by 2050 and this figure will be double in the next 20 years.[6]

Recent advancement of imaging techniques is extremely helpful for accurate diagnosis of AD at an early stage. MRI is the popular imaging modalities to study the brain anatomy and also extremely effective to differentiate the AD from the other brain related pathologies.[7-8] Measurements of Atrophy from MRI-based images are considered as predictive bio marker of disease state and progression.[9] Recently ultrahigh field MR images have contributed considerably to study of textural changes in subcortical structures of the brain.[10]

In this paper we have introduced an approach to identify the AD from normal one using texture analysis. This paper is structured in the following way: Section II provides details on of the proposed techniques. Section III provides an evaluation of this approach and the experimental results. Finally, Section IV provides conclusions of this paper.

II. METHODOLOGY

The proposed method is demonstrated in Figure 1.

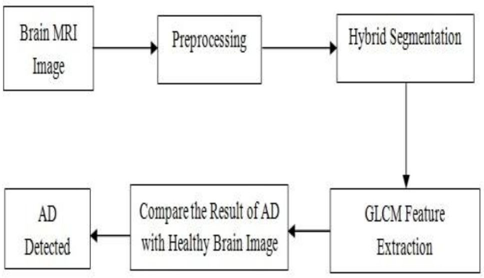

Fig 1: Block Diagram of Proposed Method

Description of the Proposed Method

The proposed method consists of three major steps: (i) Preprocessing, (ii) Segmentation, (iii) GLCM (Gray-Level Co-Occurrence Matrix) feature extraction.

(i) Preprocessing: Image preprocessing step is the most crucial and challenging part for computer-aided detection system as suppression of redundant and irrelevant data have been taken place before processing into an application. In our proposed method, image preprocessing has been divided into following steps:

a. Convert the image into gray scale image after resizing (256 X 256) the image.
b. Medical images are affected by variety types of noise. To improve the quality and feature of the image noise removal has been performed. After enhancing the contrast of gray scale image a median filter of window [3 X 3] has been applied in image for denoising.
c. Skull and brain tissue region both present in the MRI Image. Skull stripping is very important phase, in this step for better evaluation skull has been removed from the MRI image.

Algorithm for Skull Stripping

Step 1: Read the enhanced and denoising image.
Step 2: Binarize image has been obtained by using Otsu's Thresholding method.
Step 3: Mathematical morphological operations like erosion, dilation region filling have been used on the binary image.
Step 4: The final step of morphological operation is to fill the hole of resulting image.

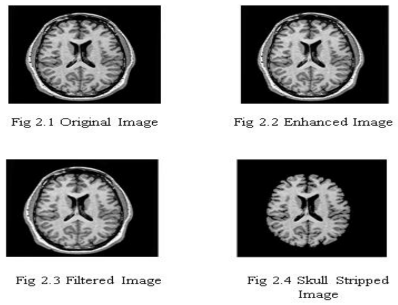

Fig 2: Preprocessed Images of Healthy Brain

Figure 2 demonstrates the out of the above steps.

Fig 3.1 Original AD Image

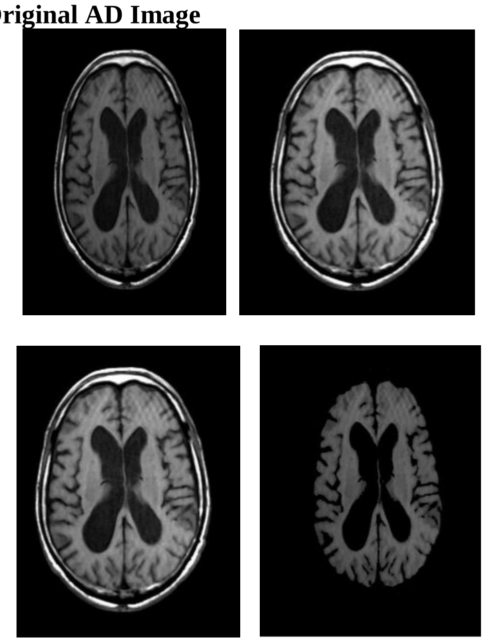

Fig 3.1 Original AD Image Fig 3.2 Enhanced Image
Fig 3.3 Filtered Image Fig 3.4 Skull Stripped Image
Fig 3: Preprocessed Images of AD

(ii). Hybrid Segmentation:
The main objective of image segmentation is to subdivide an image into meaningful regions as the divided regions can be homogeneous, non-overlapping with similar attribute like intensity, depth, color or texture.

Simple thresholding method has been applied to detect the AD from normal MRI brain image and also visible the isolated region clearly. Thresholding is the most popular segmentation algorithm due to its simplicity and efficiency. In thresholding method, a fixed constant value (T) has been selected and image replace with black pixel, if the image intensity is less than that selected constant value and white if greater than that fixed threshold value. The conditions for selecting T are given as follows:

$$g = \begin{cases} 1 \; if \; f(x,y) > T \\ 0 \; if \; f(x,y) \le T \end{cases} \qquad (1)$$

In our proposed method Otsu's method has been used to find out the threshold. It is an automatic threshold selection, region based segmentation method works on only gray value of image.

In this method optimal threshold value has been selected for maximizing the between-class variance of resulting object and background classes. The two dimensions of image is represented by the function f(x,y) and the values of it in gray-level have the range between [0...L], where L=255.
N representing the total number of pixel exists in image.

The number of pixels with gray-level i is h(i), i= [0,1,..., L] that describes the image histogram.

Histogram normalization represents the probability of occurrence of gray level i as follows:

$$p(i) = \frac{h(i)}{N}, p(i) \ge 0 \qquad (2)$$

Mean value of the image is

$$\mu_T = \sum_{i=0}^{L-1} ip(i) \sum_{i=0}^{L-1} p(i) = 1 \qquad (3)$$

Pixels will be divided into two classes like C1{ 0,1,………t} and C2{t,….L-1} when single value of thresholding has been considered.
C1 is the class of bright pixel and C2 is the class of dark pixel.
The probability of these classes can be represented as:

$$\omega_1(t) = \sum_{i=0}^{t-1} p(i) \qquad (4)$$

$$\omega_2(t) = \sum_{i=t}^{L} p(i) \qquad (5)$$

And the mean can be explained as

$$\mu_1(t) = \sum_{i=0}^{t} ih(i)/\omega_1(t) \qquad (6)$$

$$\mu_2(t) = \sum_{i=t}^{L-1} ih(i)/\omega_2(t) \qquad (7)$$

Optimal threshold t^* is

$$t^* = Arg\,max_{0 \le t \le 255}\{\sigma_B^2(t)\} \qquad (8)$$

Where between-class variance $\sigma_B^2(t)$ can be defined as:

$$\eta(t) = \sigma_B^2(t) \qquad (9)$$

$$\sigma_B^2(t) = \omega_1(t)(\mu_1(t) - \mu_T)^2 + \omega_2(t)(\mu_2(t) - \mu_T)^2 \qquad (10)$$

Morphological operations:

(a) Boundary Extraction: The objective of boundary extraction is to find the pixels that are on the boundary of objects in the image. In our algorithm boundary extraction has been taken palace on the resultant image.

The boundary of a set *A*, denoted as *β(A)*, can be obtained by first eroding *A* by *B* and then performing the set difference between *A* and its erosion as follows:

$$\beta(A) = A - (A \Theta B) \qquad (11)$$

(b) Dilation: Dilation has been applied to represent the expansion of boundaries of its foreground pixels regions.

A and B sets in Z^2, the dilation of A by B , denotes as $A \oplus B$, is defined as

$$A \oplus B = \{z | (\hat{B}_z) \cap A \# \emptyset\} \qquad (12)$$

The dilation of A by B then is the set of all displacements, z, as there will be overlap by at least one element of A and B. Based on this interpretation Eq. (3) can be written

$$A \oplus B = \{z | [(\hat{B})_z \cap A] \subseteq A\} \qquad (13)$$

Watershed Segmentation: Watershed segmentation has been used in our proposed method as it provides the close contours. It is very simple and powerful segmentation tool to group the pixel of similar intensities. It is a gradient based segmentation. The steps of watershed segmentation are as follows:

(i) Gradient magnitude is computed from the input image
(ii) Next, watershed is computed of gradient magnitude.
(iii) Finally superimpose operation of the gradient has been performed on the original image

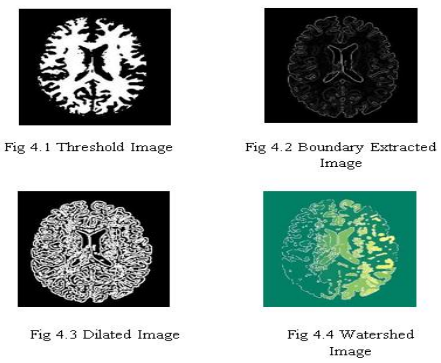

Fig 4.1 Threshold Image
Fig 4.2 Boundary Extracted Image
Fig 4.3 Dilated Image
Fig 4.4 Watershed Image

Fig 4: Images of Hybrid Segmentation for Healthy Brain

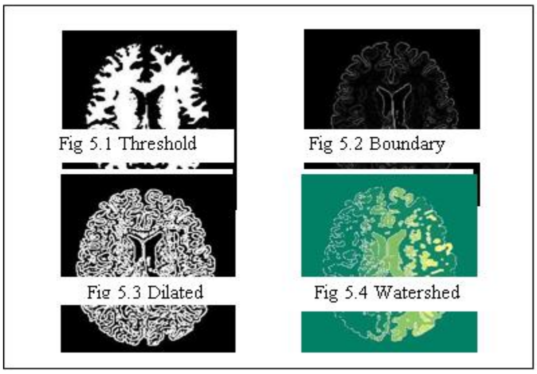

Fig 5: Images of Hybrid Segmentation for Healthy Brain

III. Feature Extraction

Features describes the properties of image and also important characteristics to identify the objects or regions of interest. The purpose of the feature extraction process is to detection and isolation the desired region by measuring the curtain features instead of computing the features of large set of data.

(iii) GLCM (Gray Level Co-Occurrence Matrix):

GLCM is the popular second order statistical texture feature which is used for extracting the features from the image considering the spatial relationship of the pixels. The number of rows and columns are equal of gray levels of image. The texture of an image has been characterized by GLCM functions aiming to calculate how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. The fourteen textural features proposed by Haralick et all [R.M. Haralick, K. Shanmugam, I. Dinstein, "Textural Features for Image Classification", IEEE Trans. on Systems, Man and Cybernetics (1973) 610 – 621] by calculating the co-occurrence matrix. In this paper four important GLCM texture features that are extracted are as follows:

(i) Energy: It measures the textural uniformity, that is, measure of pixel pair repetitions. Range= [0 1].

$$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j)^2 \qquad (14)$$

(ii) Contrast: It measures the intensity contrast between a pixel and its neighbor of the whole image. Range=[0 1]

$$\sum_{n=0}^{N_g-1} n^2 \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j)^2 \qquad (15)$$

(ii) Correlation: Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other over the whole image. Correlation is 1 or -1for a perfect positively or negatively correlated image. Range= [-1 1]

$$C = \frac{1}{\sigma^x \sigma^y}\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i,j)p(i,j)^2 - u_x u_y \qquad (16)$$

Homogeneity: It is also defined as Inverse Difference Moment. It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM. Range= [0 1]

$$H = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{p(i,j)}{(1+mod(i,j))} \qquad (17)$$

Table 1: Evaluation of AD and normal MRI brain image using GLCM

Features	AD	Normal
Energy	0.4101	0.5338
Contrast	0.3475	0.1157
Correlation	0.9868	0.9901
Homogeneity	0.9882	0.9850

Table 1 represents the GLCM value for AD and normal brain.

IV. CONCLUSION

In this method an efficient approach has been has been represented to identify the Alzheimer's disease at an early stage from the MRI image which help in successful therapy and treatment planning. This hybrid segmentation based textural analysis method offers a promising result for detecting and discriminating AD from the healthy brain. The proposed diagnostic method is an alternative to traditional human-based technique and also helpful to make a faster and accurate decision of presence and absence of disease by using this non-invasive methodology. This promising complementary model, enhancing and supporting the performance and accuracy of this method. The key feature of this method is not only able to detect the AD but also capable to diagnosis other brain related abnormalities.

V. REFERENCE

1. K.D. Desai1, S. Parmar, Effective early detection of Alzheimer's and Dementia disease using Brain MRI Scan Images, International Journal of Emerging Technology and Advanced Engineering , Volume 2, Issue 4, April 2012.
2. S.Mareeswari1, G.Wiselin Jiji, A SURVEY: EARLY DETECTION OF DISEASE USING DIFFERENT TECHNIQUES, International Journal on Computational Science & Applications (IJCSA), Vol.5, No.1, February 2015.
3. S. Akhondzadeh, M. Noroozian, Alzheimer's disease: pathophysiology andpharmacotherapy, IDrugs: the investigational drugs journal, 2002; 5(11): 1062–1069.
4. LE Hebert, J Weuve, PA Scherr, DA Evans, Alzheimer disease in the United States (2010-2050) estimated using the 2010 Census. Neurology, 2013; 80(19): 1778-83.
5. Association. Early-Onset Dementia: A National Challenge, a Future Crisis. Washington, D.C.: Association; 2006.
6. D Zhang, Y Wang, L Zhou, H Yuan, D Shen , Multimodal classification of Alzheimer's disease and

mild cognitive impairment, NeuroImage, 2011; 55: 856–867.
7. A. Ray, S. K. Bandyopadhyay, ‘A Review on MRI Based Automatic Brain Tumor Detection and Segmentation’, International Research Journal of Engineering and Technology, 2016; 3(7): 1574-1589.
8. A. Ray, S. K. Bandyopadhyay, ‘Automatic Detection of Ischemic Stroke Lesion Using Textural Analysis from Brain CT Images’, European Journal of Biomedical & Pharmaceutical Sciences, September 2016; 3(10): 282-288.
9. A. Ramani, J. H. Jensen, J. A. Helpern, Quantitative MR Imaging in Alzheimer Disease, Radiology, 2006; 241(1): 26-44,
10. Doan, Nhat Trung, et al., Texture analysis of ultrahigh field T2*-weighted MR images of the brain: Application to Huntington's disease." Journal of Magnetic Resonance Imaging, 2013.