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Hippocampus Segmentation of Brain MRI Images for Possible Progression Detection of Alzheimer's Disease

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ABSTRACT

Alzheimer's disease (AD) has become as one of the most serious ailments that need to be faced by people all over the world. There is no cure for AD, but the progression of the illness may be reduced with the early detection and proper monitoring of the disease. Many current studies focused more on early detection but does not include the monitoring process as well. Proper monitoring system is as critical as early diagnosis since it allows doctors to assess the disease development of Alzheimer's patients quantitatively. This study proposes to develop an algorithm for detecting the hippocampus of patients with Alzheimer's disease in MRI images and use that for the purpose of progression detection of the disease. After performing some pre-processing steps, the active contour method (Chan-Vese) was used to extract the region of interest (ROI). Next, certain parameters were calculated including the number of pixels and area pixels. From the extracted parameters of the patients from two different MRI sessions, percentage of progression is calculated by measuring the reduction in pixel numbers from those images. This study was able to develop a semi-automated and robust model based on the Chan-Vese segmentation technique, where it could observe the shrinking of the patient brain by the progression method using the total pixels of the hippocampus and its area by getting decreased at the second visit. Based on the result, it shows that this study could be further extended by implementing various feature extraction techniques to come out with a more robust output which can be used for progression detection of Alzheimer's disease.

1. Introduction

Alzheimer's disease (AD) has become one of the most common illnesses that individuals endure. It typically affects those above the age of 65, and it is a form of dementia caused by a neurodegenerative disorder [1]. The disease progresses through various phases, from mild to

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moderate to severe. The illness begins off mild and worsens over time. The illness causes two regions of the brain to shrink and the ventricles to expand in the brain. The hippocampus and cerebral cortex are the two components that are involved. The cytoskeletal alterations in AD are extensively spread, and the medial temporal lobes and neocortical association regions are severely damaged.

Damage to the hippocampus and cerebral cortex affects the brain area responsible for judgements, planning, reasoning, and remembering [2]. The laboratory diagnosis of AD is typically accompanied by structural alterations, beginning with the entorhinal cortex and hippocampus inside the temporal lobe of the brain and progressing to neocortical areas. The temporal lobe of the brain, particularly the medial temporal lobe (MTL) components, is critical for information consolidation and the creation of short-term and long-term memory [3]. The hippocampus, which sits through the length of the MTL and belongs to the limbic system, is a significant component of memory circuitry and is one of the first regions to be affected by AD [4]. Figure 1 displays the hippocampus and cerebral cortex position in the brain through Magnetic Resonance Imaging [5].

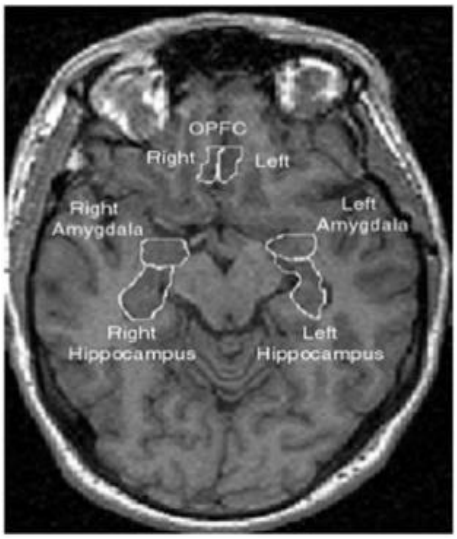


Fig. 1. Hippocampus in the brain and its position [5]

Magnetic Resonance Imaging (MRI) is an imaging modality that is widely utilized for imaging-based brain tumor identification. The MRI technique is used to produce a detailed image of a human body organ. In broad terms, structural MRI in AD can be divided into assessing atrophy (or volumes) and changes in tissue characteristics that cause signal alterations on certain sequences, such as white matter hyperintensities on T2-weighted MRI resulting from vascular damage. MRI has been proven to be very useful in assessing pathological tissues in AD [6-8]. Structural MRI can identify disease-induced structural changes in the brain, assisting in the diagnosis of Alzheimer's disease. For the AD classification challenge, MRI image characteristics derived from hippocampus regions are typically employed [3].

It is critical to understand how the disease begins and progresses to create therapeutic measures targeted toward prevention [9]. AD cannot be cured, although the progression of the illness can be reduced. However, there is yet to be any study on building a monitoring system for AD that can continually monitor Alzheimer's patients to identify any progression signs based on hippocampus areas. Besides that, for such a system to be developed, a thorough investigation needs to be performed on the AD data from multiple patient visits to the hospital.

Therefore, this study would like to develop an algorithm for segmenting the brain hippocampus from MRI images to detect AD progression. To develop such an algorithm, specific image processing,

and analysis techniques were performed to segment the hippocampus of brain MRI images taken from the ADNI database [10-12]. Segmentation of the hippocampus, also known as diffuse brain atrophy, which includes atrophy of the cerebral cortex and atrophy of the medial temporal lobe (MTL) components, is a significant pathogenic feature of Alzheimer's disease that can play a critical role in the accuracy of detecting or progressing the disease [7]. Then, a segmentation algorithm could be built to investigate the progression of the disease from time to time.

2. Methodology

Figure 2 shows the block diagram of the entire study and its process. The MRI images of the brain were acquired from the Alzheimer's disease neuroimaging initiative database (ADNI). Several image pre-processing methods were implemented before the hippocampus areas of the brain were then segmented. Finally, the parameter for progression detection of AD was calculated. The detail of each process is explained in the following sections.

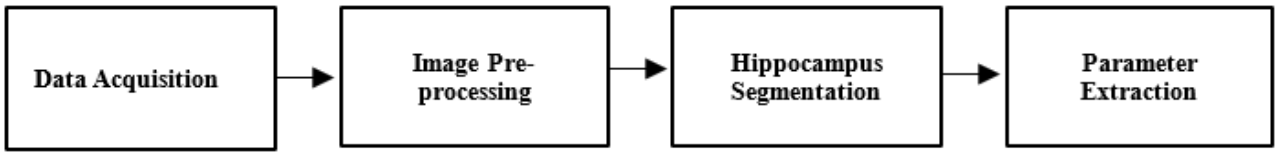


Fig. 2. Block diagram of the study

2.1 Data Acquisition

The MRI data of AD patients used in this study are gathered from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI was launched in 2003 as a public-private partnership, led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD). For up-to-date information, see www.adni-info.org.

In this study data of AD patients has been collected, and data set selection was made based on the data from patients' multiple visits or at least 2 visits to the hospital, for the purpose of progression detection of the disease. For this study, 20 sets of images coming from patients with at least 2 visits were used to be tested.

2.2 Image Pre-processing

For each set of data, the hippocampus is only found in a small portion of each slice. Therefore, just a few slices from each sample are chosen for manual screening, where it can be recognized clearly at a range of slices num 63 – 67 in each data set. In addition, several steps need to be placed such as the thresholding level (binarization) which is the Luminance threshold, specified as a number in the range [0, 1], and the range in this project was set at 0.4-0.6 depending on the original image intensity and due to black and white images used which is the standard range.

Then, the images underwent the filtering process. Various types of filters are used in image processing. Some filters include Median, Wiener, CLAHE, Histogram Equalization, and Gaussian Low Pass filter [13-18]. They may boost the contrast of the images that have been converted to grayscale but still have a low contrast level. The filter tries to maintain the image's basic structure while

removing unimportant minor features. Filters may also be used to decrease image noise, remove haze, and mat images, among other purposes [19]. The capabilities of the filters were evaluated by calculating the value of Mean Squared Error (MSE) and Power Signal to Noise Ratio (PSNR). The MSE and PSNR of the filtered images can be calculated by using Eq. (1) and Eq. (2) respectively.

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)] \quad (1)$$

$$PSNR = 20\,log_{10}(MAX\,I) - 10\,log_{10}(MSE) \quad (2)$$

where *I(i,j)* and *K(i,j)* are the output and input images, respectively, *M* and *N* are the size of the image (length and width, respectively), and $MAX\ I$ (Peak Value) is the maximal in the image data. If it is an 8-bit unsigned integer data type, the peak value is 255.

2.3 Hippocampus Segmentation

The partitioning of a digital image into several regions is known as image segmentation. The goal of segmentation is to simplify and/or alter an image's representation such that it is more relevant and simpler to analyze. Image segmentation is a technique for detecting objects and boundaries (lines, curves, and so on) in images. The process of separating an image into regions, or segments, that are recognizable, accessible, actionable, useful, and have the potential for development is referred to as segmentation. Figure 3 shows the segmentation process for this particular study. As shown in Figure 3, active contour algorithm is used to extract the parameters of ROI (hippocampus) via several steps after the image has been prepossessing for more enhancement by deforming the initial border of an item in an image to latch onto typical features inside the region of interest given an approximation of the object's boundary. This technique is based on Chan-Vese active contour without edges [20,21]. It is repeatedly extended until it matches the border of the ROI by going on to the ROI selection. The concept of interactive region selection is utilized to allow the user to decide the ROI based on their needs. Then once the ROI was defined manually by using the selecting tool, the algorithm was applied to the chosen region. To detect just the hippocampus, the first contour should be generated inside the region of interest. So, to reach this point the ROI surrounding should be identified by cropping the middle area of the brain and initiating the contour through it to get the final shape of the hippocampus.

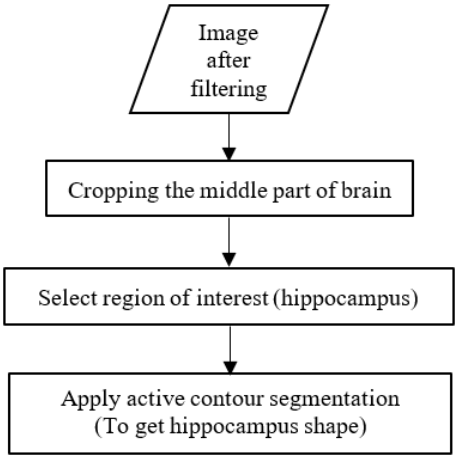


Fig. 3. Segmentation Process

2.4 Parameter Extraction

By extracting the hippocampus shape, the algorithm will be able to determine the parameters, such as the number of pixels, area pixels, and its mean value, using the region props function to provide the MajorAxisLength of the blob in the image segmentation performance. Parameter's extraction can then be used to estimate the extent of the patient's Alzheimer's progression by using the following Eq. (3).

$$Progression = \frac{|1st\ total\ pixels - 2nd\ total\ pixels|}{1st\ total\ pixels}\ x\ 100 \quad (3)$$

3. Results

Figure 4 shows four different images, each filtered by a different filter, namely Median Filter, CLAHE, Histogram Equalization, and Gaussian low pass Filter. The median filter is efficient for smoothing spiky noise, Moreover, it preserves the edges during noise removal. CLAHE filter enhanced the contrast by acting on a tiny region of the image called tiles, and then combines nearby tiles using bilinear interpolation to minimize the artificial borders. On the other hands, Histogram Equalization works by modifying the image contrast. Gaussian low pass filter reduced the nose and a bit blur it so it seems more realistic to the original image.

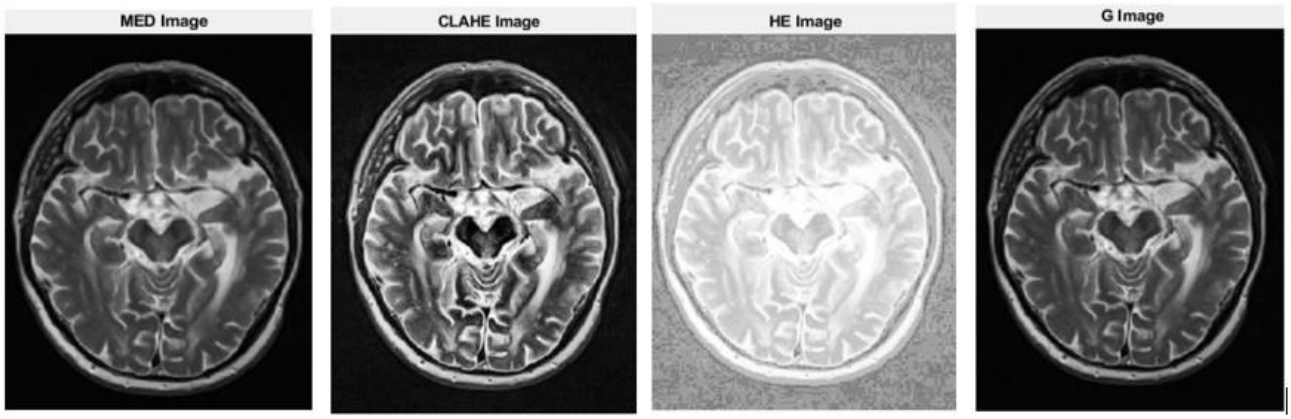


Fig. 4. Filtering process output using Median filter, CLAHE filter, Histogram Equalization filter and Gaussian Low Pass filter

Table 1 show the result of calculated MSE and PSNR for the output images. Based on the Table 1, the best filter was Gaussian LPF, with a superior peak signal-to-to-noise ratio (PSNR). The better the image quality, the greater the PSNR value. In computing the Mean Square Error (MSE), the difference in the squared difference between the compressed and uncompressed images is measured. It is preferable to have a lower MSE value since it creates more minor errors, and the Gaussian LPF produced a low value compared to other filters which are 2.31 where is the highest one was the HE filters by 16928.79. The Gaussian LPF is the best filter compared to the others because it produces a high value of PSNR by 44.5 dB and a low value of MSE.

Figure 5 shows how Chan-Vese active contours are used for iterative segmentation of the hippocampus as areas of interest from MRI images. As a consequence, the object's contour may be identified, allowing for more exact segmentation, where the hippocampus and the features can be detected and segmented using the proposed method. As shown in Figure 5, the hippocampus was

shaped by the proposed method and the targeted area are filled in successfully as required, which help to extract the parameters.

Table 1
The values of MSE and PSNR for all filter types

Filter types	MSE	PSNR
Median filter	10.45	37.97 dB
CLAHE filter	564.09	20.65 dB
Histogram Equalization filter	16928.79	5.87 dB
Gaussian Low Pass filter	2.31	44.53 dB

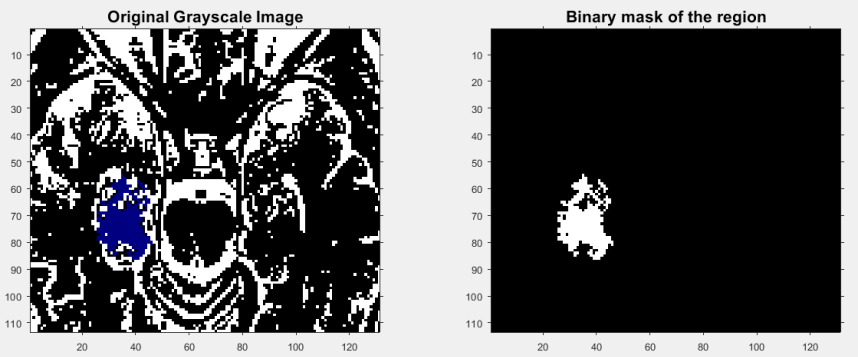
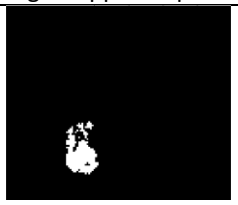
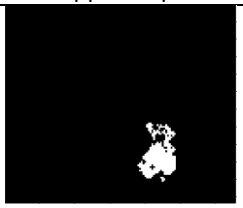
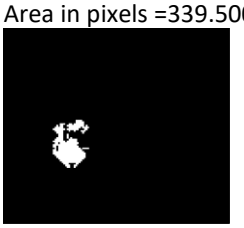
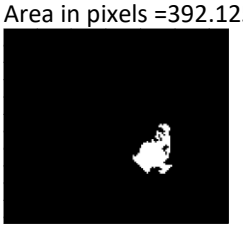


Fig. 5. Segmented image

Table 2 shows the samples of the segmented shapes of the hippocampus and its number of pixels with pixels area for both left and right hippocampus. Then, in order to demonstrate the patient's results of the increased progression the percentage of progression is calculated. The progress is calculated from the total number of pixels for both hippocampi between two visits. The progression can be identified in the result in which the total pixels of the hippocampus and its area got decreased at the second visit as shown in Table 2. The first visit the total number of the pixels was 707 then in the second visit it shows 650 so the progression percentage 9%, calculated by1st MRI total pixels minus the 2nd MRI total pixels, then divide it with the 1st MRI total pixels multiplied by 100.

Table 2
The calculation of the pixel area, and the percentage of progression

Data List	Right hippocampus	Left hippocampus	Total Num
1st Visit			707
	Number of pixels=330 Area in pixels =339.5000	Number of pixels=377 Area in pixels =392.1250	
2nd Visit			650
	Number of pixels=317 Area in pixels =327.3750	Number of pixels=340 Area in pixels =350.3750	
Progression = 9%			

4. Conclusions

In conclusion, this project was able to identify the best type of filter through the MSE and PSNR values, which helped develop an algorithm for the segmentation of hippocampus in MRI images for Alzheimer's disease. In this research study, a semi-automated and robust method was proposed for segmenting the hippocampus from different MRI Images (patients) using the Chan-Vese segmentation technique. Moreover, Chan-Vese has been incorporated for performing the region of interest (ROI) based segmentation and obtaining the desired results at respective iterations by extracting the hippocampal shapes and measuring the parameters needed to determine the progression percentage, which is yielding promising segmentation results and is a useful achievement. For further recommendation, thorough feature extraction and analysis could be performed to the images to seek for other possible prominent features that could be used for possible progression detection of AD.

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*Data used in preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf

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