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Hybrid Segmentation Algorithm for Detecting Alzheimer's Disease in MRI Images

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ABSTRACT: Alzheimer is defined as the loss of mental functions such as thinking, memory, and reasoning that is severe enough to interfere with a person's daily functioning. The appearance of Alzheimer's Disease symptoms are resulted based on which part of the brain has a variety of infection or damage. Therefore, MRI is the best biomedical instrumentation to detect Alzheimer's Disease. For that reason, this paper proposes a novel method for detecting Alzheimer's Disease in MRI images using thresholding and morphology. In this paper, we analyzed 20 MRI images collected from OASIS brains database to detect the threshold that will allow our program to automatically detect Alzheimer's Disease existence in MRI images. Automatically Image Classification is one of the challenging problems of our recent era. So, we have implemented and tested our proposed technique and the end results have 98% accuracy.

KEYWORDS: Alzheimer's Disease, MRI, biomedical images, image processing, thresholding, masking, morphological operators.

1 INTRODUCTION

Worldwide, more than 35 million people are diagnosed with Alzheimer's disease, and that number is expected to double in the next 20 years [1]. Alzheimer's Disease (AD) is a progressive irreversible neurological brain disorder, that gradually damages memory, thinking, and language skills. AD symptoms include changes in mood, behavior, or personality and difficulty doing familiar daily tasks. Generally, AD affects not only patients but also people around them [2].

The brains of people diagnosed with AD face the problems of tissue loss and nerve cell death, leading to brain dramatic shrinkage. The affected brain areas include the cortex, which is responsible for thinking, planning and remembering, and the hippocampus, that forms new memories. Consequently, ventricles grow larger.

Since AD is gradual, the key to treatment is early diagnosis. The medical and neurological examination comprises semi-structured interviews with the patient, and separately with a collateral source that knows the patient. The patient's cognitive and functional performance in different six domains is rated and summed to yield the Clinical Dementia Rating (CDR). A CDR of 0 indicates Normal Cognitive (NC) functioning, whereas CDR of 1 indicates AD [3].

Moreover, the workup contains brain imaging using different techniques; such as Computed Tomography (CT), Positron Emission Testing (PET), or Magnetic Resonance Imaging (MRI) for detecting structural abnormalities of human brain [4]. In particular, structural MRI measurements help in detecting and tracking the evolution of brain atrophy, which is considered as a marker of AD development.

An important aspect of MRI image processing that can be used for AD diagnosis is segmentation, due to its capability of extracting objects of interest [5]. Therefore, we propose in this paper a novel hybrid segmentation algorithm for AD detection in MRI images. The rest of this paper is organized as follows. Section II reviews the literature of AD detection in medical images specifically MRI images. Then, Section III elaborates about the data sample we used and the source of MRI images. Section IV describes in details the proposed technique. Then, section V explains the used classification criteria. Section VI discusses and evaluates the experimental results. Finally, Section VII provides a summary of the paper and its main conclusions.

2 LITERATURE SURVEY

Existing work in the field of AD detection in MRI images has been partially positive. The problem of AD recognition in structural MRI images using visual similarity was tackled in [6]. Visual local descriptors and the bagof-visual-words approach were applied on Hippocampus and Posterior Cingulate Cortex in brain MRI images. Then, the Content-Based Visual information retrieval approach is applied to recognize patient category. The findings can be used to support clinicians' diagnostic decision. And, accuracy on MCI case retrieval was improved by 10%.

AD classification method in MRI images was presented in [7]. Furthermore, the authors offered a tool to assist early diagnosis of dementia using wavelet feature extraction. The results showed that dimensionality reduction decreases classification accuracy, which suggested using all of the available information to perform classification, which in turn could increase computational cost in the training of the classifiers.

Mild Cognitive Impairment (MCI) recognition approach using MRI images was proposed in [8], where Grey Matter (GM) was segmented and Local Patterns was extracted from it. However, a perfect local pattern could not be identified.

The detection of AD onset in MRI images was presented in [9]. Three different machine learning algorithms were combined to get improved results. An average training accuracy of 94.57% and a testing accuracy of 87.23% were achieved, indicating the method's efficiency in detecting the onset of AD.

Finally, three major medical imaging techniques that are associated with AD were analyzed and evaluated in [10]. Those techniques are CT, PET, and MRI. The results showed that MRI is more beneficial than the others. The paper presented as well a mechanism to estimate hippocampal atrophy using ImageJ to indicates AD presence. Therefore, we chose to proceed with developing an algorithm working specifically on MRI images.

3 IMAGE DATABASE

We obtained (n = 20) MRI brain scans from the publicly available Open Access Series of Imaging Studies (OASIS) database. All images were axial and of 256x256 size. The 20 subjects included 10 normal controls (NC) aged 60 years old or above with a CDR scale of zero; and 10 subjects clinically diagnosed with AD with CDR = 1. All subjects were right-handed. Sample demographics including age, Mini-Mental State Examination (MMSE) scores, and gender are summarized in Table 1.

Table 1. Sample Demographics

	Age	**MMSE**	**Gender**
NC (CDR = 0)	Average = 64 STD = 10.31988	Average = 28.8 STD = 1.643168	7 F 3 M
AD (CDR = 1)	Average = 83.8 STD = 3.768289	Average = 25 STD = 2.915476	8 F 2 M

4 METHODOLOGY

The proposed technique was built based on comparing the ratio of high intensity pixels to low intensity ones in both NC and AD MRI images. The block diagram in Fig.1 expresses the steps in our method.

Fig. 1. Proposed Method Block Diagram

4.1 THRESHOLDING

Segmentation implies dividing an image into regions. Thresholding is considered as one of the simplest image segmentation methods as it is based on selecting a certain value called threshold; which classifies image pixels into two distinct groups in order to isolate the object of interest from the background [11].

Thresholding results in binary images by turning all pixels in the grayscale input image that fall below the threshold to zero and all pixels above that threshold to one. If *g(x, y*) is a thresholded version of *f(x, y)* at some threshold *t*,

$$g(x,y) \quad \begin{cases} 1 \; if \; f(x,y) \geq \tau \\ 0 \; otherwise \end{cases} \qquad (1)$$

In our process, the threshold is found using Otsu's method, which selects the optimal threshold value that maximizes the inter-class variance of foreground (i.e. object of interest) and background classes [12].

$$\tau^{*} \quad arg\,max_{0 \leq t \leq 255}\{\sigma_B^2(t)\} \qquad (2)$$

The inter-class variance is defined as,

$$\sigma_B^2(\tau) \quad \omega_1(\tau)(\mu_1(t) \quad \mu_T)^2 + \omega_2(t)(\mu_2(T) \quad \mu_T)^2 \qquad (3)$$

While the class probability is computed from the histogram as,

$$\omega_1(t) \quad \sum_0^{t-1} p(i) \qquad (4)$$

$$\omega_2(t) \quad \sum_t^{L} p(i) \qquad (5)$$

And the class mean is,

$$\mu_1(t) \quad \frac{\sum_0^{t-1} i\,p(i)}{\omega_1(t)} \qquad (6)$$

$$\mu_2(\tau) \quad \frac{\sum_t^{L} i\,p(i)}{\omega_2(t)} \qquad (7)$$

Where $L \quad 255$ and τ is the threshold. Selecting the threshold is done successively until finding the optimal value. Fig. 2 (a) shows the original MRI image and Fig. 2 (b) shows the thresholding result.

(a) (b)

Fig. 2. (a) Original Brain MRI Image (b) Thresholding Result

In this case, our object of interest is the brain. However, the scalp bones are appearing clearly in Fig. 2 (b) and we will demonstrate in the next steps how to eliminate them from the image.

4.2 EDGE DETECTION

Edge detection identifies and locates abrupt changes in pixel intensity in an image. These discontinuities characterize boundaries of objects in the image. The majority of edge detectors are based on the gradient method that finds the minimum and maximum in first-order derivative of the image intensity, because they contain valuable edges information [13]. Gradient based detectors include Prewitt filter that contains a pair of 3×3 convolution kernels as shown in Fig.3. These kernels detect vertical and horizontal edges, using the appropriate mask [14].

In our method, we use Prewitt operator to detect the edges of the scalp bones, as shown in Fig. 4.

4.3 DILATION

Mathematical morphology involves analyzing and processing geometrical structures within an image. The structure could be of a macro nature or a micro nature [15]. The basic morphological operators include dilation, which can be applied to binary images in order to expand the boundaries of foreground pixels regions. Hence, the growth of foreground pixels areas results in filling the holes within those regions.

In this algorithm, we apply dilation in order to create a mask that can be used for removing scalp bones in order to isolate our Region of Interest (ROI) which is the brain. After performing dilation on Fig. 4, the result is shown in Fig. 5 (a). Then, we proceed by detecting and deleting the small white regions in the resulting image to get the result shown in Fig. 5 (b). Finally, we complement the aforementioned image to create the mask that will be used for removing scalp bones. The result is shown in Fig. 5 (c).

-1	0	+1
-1	0	+1
-1	0	+1

(a) Gx

+1	+1	+1
0	0	0
-1	-1	-1

(b) Gy

Fig. 3. Masks for Prewitt Filter (a) In the x-direction (b) in the y-direction

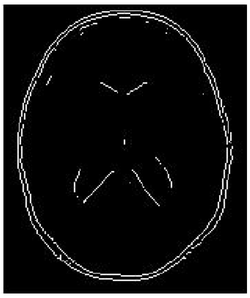

Fig. 4. Prewitt Filter Application Result

(a) (b) (c)

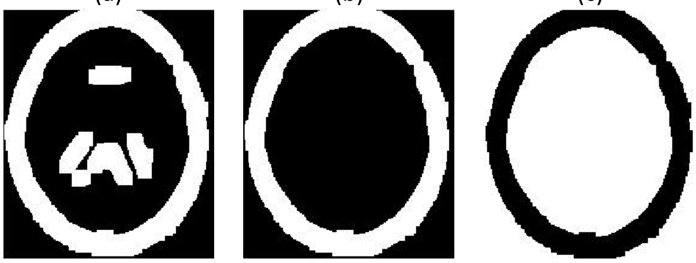

Fig. 5. (a) Dilation Result (b) Clearing Small White Regions Result (c) Resulting Mask

4.4 USING THE MASK IMAGE

After obtaining the mask image, we use it to mask the thresholded image shown in Fig. 1 (b) by performing a logical and operation. The end result is shown in Fig. 6.

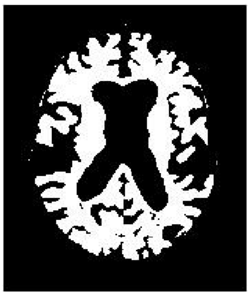

Fig. 6. End Result

4.5 Image Cropping

We found that isolating the Corpus callosum by cropping the resulting image yields the best readings when trying to classify the end results. We did the cropping by dividing the image into two halves vertically and three thirds horizontally and take the middle lower part.

5 Classification

For each image, we calculated the ratio of the number of high intensity pixels to the number of low intensity pixels in the ROI. Then, we compared the ratios of NCs to AD affected brains. The chart shown in Fig. 7 lead us to detect the threshold number that we used to classify whether the patient has AD or not, and give the appropriate result accordingly.

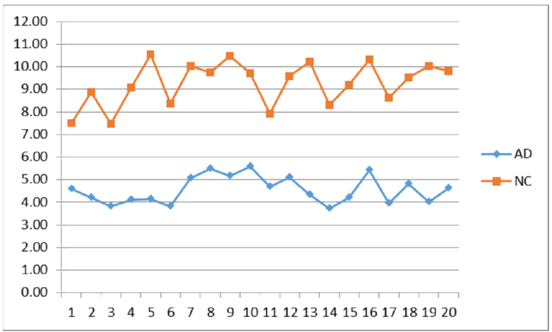

Fig. 7. Ratio of White Cells to Black Cells in Healthy Brain Images and AD Affected Images

6 Experimental Results

Appling our proposed method on (n=20) MRI brain scans for subject older than 60 years old yielded 98% accurate results.

7 Conclusion

In this paper, we presented a novel method for AD detection and classification in MRI images based on thresholding and morphological operators. The method was applied to 20 MRI brain images from the Oasis AD database and yielded 98% accurate results. Furthermore, we found an optimal ratio threshold that can be useful to differentiate between AD and NCs, which indicates its efficiency in detecting AD.

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