Detection of Alzheimer Disease Using Zernike Moments

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Abstract- Alzheimer's disease (AD) is a common progressive neurodegenerative disorder that is not currently diagnosed until a patient reaches the stage of dementia. It's most common type of dementia among older people. There is an urgent need to identify AD at an earlier stage, so that treatment can begin early. The transitional state between healthy control (HC) and AD with mild memory problems is Mild cognitive impairment (MCI). A reliable diagnosis of MCI can be very effective for early diagnosis of AD. In this paper we use the fast recursive method for the classification of MRI features from AD, MCI & HC with ZMs and different classifiers are observed for accurate classification of HC/AD and HC/MCI. We worked with 210 MRIs from the database of the Alzheimer's disease Neuroimaging initiative (ADNI 1 1.5T). The one slice of 210 MRIs used in this study included 70 AD patients, 172 MCI patients and 70 HC individuals. We have selected 50% of the MRIs randomly for use in training classifiers and rest 50% for the testing phase. The technique used here yielded the best overall classification results between AD and MCI using ZMs (accuracy 87.143%) and for pairs of the MCI and HC using ZMs (accuracy 81.429%). Detailed experiments are carried out for the diagnosis of MCI individuals from AD and HC groups using structural MRI.

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Index Terms: - Alzheimer, Mild cognitive impairment, Healthy control, Zernike Moments.

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1. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease of the brain that causes changes in brain functions. AD usually affects people over the age of 65 years, resulting in a progressive decline in memory as well as, thinking, language and learning capacity. Age is the strongest predictor for the development and progression of AD; with the rapidly aging population of our society, AD clearly poses a major health problem [1]. The path physiology of AD is related to the injury and death of neurons, especially in those areas of the brain involved with memory and learning. AD is the most common form of dementia, accounting for 50% to 75% of all dementia cases, with a greater proportion older populations. AD among should be differentiated from normal age-related declines in cognitive function, which are more gradual and associated with less disability. AD often starts with mild symptoms and ends with severe brain damage. People with dementia lose their abilities at different rates. On average, AD patients live from 8 to 10 years after being diagnosed, although the disease can last for as many as 20 years [1, 2]. Mild cognitive impairment (MCI) is a transitional state between normal aging and dementia. MCI is associated with an increased risk for dementia. Such patients are able to live independently, are aware of their memory changes, and typically show problems with delayed recall, although non memory cognitive domains can also be impaired [3, 4].

Advances in medical technology have helped increase life expectancy, but age-associated cognitive impairment often diminishes the quality of life for the increasing numbers of older adults. AD is currently the most common form of dementia. . In 2005, an estimated 24 million people around the world suffered from dementia. According to the 2010 World Alzheimer report, an estimated 35.6 million people worldwide are living with dementia at a total cost of more than US\$600 billion in 2010, and the incidence of AD throughout the world is expected to double in the next 20 years [5, 6]. By 2040, it is predicted that more than 81 million people worldwide will suffer from dementia. Deaths, because of AD have been rising dramatically while other major causes of death have been on the decline. AD is the sixth leading cause of all deaths in the United States and the fifth leading cause of death in Americans aged 65 years and older. Between 2000 and 2008, deaths due to AD increased by 66% whereas heart disease deaths decreased by 13%, stroke deaths by 20%, and prostate cancer-related deaths by 8% [5, 6].

AD inflicts a terrible toll on patients, their families, and society in general. Most experts agree that treatment is most beneficial if applied early, before significant, potentially irreversible neurodegeneration and functional impairment has occurred [4, 5]. Over the coming decades, the baby boom population is projected to add 10 million people to these numbers. By 2050, the incidence of AD is expected to approach nearly a million people per year, with a total estimated prevalence of 11 to 16 million people. Dramatic increases in the numbers of "oldest-old" (those aged 85years and older) across all racial and ethnic groups will also significantly affect the numbers of people living with AD while the number of Americans aged 65 and over with AD is projected to reach 13.2 million in 2050 compared with 4.5 millions in 2000. If present trends continue, the cost of caring for the expected increase in the number of AD patients will bankrupt public healthcare systems [4, 5].

AD can affect different people in different ways, but the most common symptom pattern begins with gradually worsening difficulty in remembering new information as the disruption of brain cell function usually begins in regions involved informing new memories. As damage spreads, individuals experience other difficulties. The following are warning signs and symptoms of AD [3-5]:

- i. Memory loss that disrupts daily life.
- ii. Challenges in planning or solving problems.
- iii. Difficulty completing familiar tasks at home, work, or leisure.
- iv. Confusion with time or place.
- v. Trouble understanding visual images and spatial relationships.
- vi. New problems with words in speaking or writing.
- vii. Misplacing things and losing the ability to retrace steps.
- viii. Decreased or poor judgment.
- ix. Withdrawal from work or social activities.
- x. Changes in mood and personality.

The methods used for early detection of AD include clinical tests, as well as computerized tomography (CT), magnetic resonance imaging (MRI), single photon emission computed tomography (SPECT), positron emission tomography (PET), and cerebrospinal fluid (CSF) biomarkers [5-7]. Traditionally, neuroimaging techniques have been categorized as either structural or functional, according to the primary information they provide. However, methods generally used to look at structure can also be altered to observe function (e.g., functional MRI). In this paper we use the ZMs as a training algorithm as ZMs have a powerful feature extractor in pattern recognition due to their high robustness to noise and their good performance in recognizing circular shapes [8].

The work in this paper is organized by describing the basic formulation of ZMs in section 2. Section 3 describes the various classifiers. Detailed experimental analysis is presented in section 4 followed by the conclusion in section 5.

2. ZERNIKE MOMENTS

Zernike introduces a set of complex polynomials which form a complete orthogonal set over the interior of the unit circle, i.e. $x^2 + y^2 \le 1$. The two dimensional Zernike moment of order p with repetition q over a unit disc is given by

$$Z_{pq} = \frac{p+1}{\pi} \iint_{x^2 + y^2 \le 1} f(x, y) V_{pq}^*(x, y) \, dx \, dy.$$
(1)

where

p positive integer or zero

q positive and negative integers subject to constraints $p - |q| = \text{even}, |q| \le p$

The functions $V_{pq}^{*}(x, y)$ are the complex conjugate

of Zernike polynomial $V_{pq}(x, y)$ which is

orthogonal and complete. It is defined as

$$V_{pq}(x, y) = R_{pq}^{Z}(x, y) e^{jq\theta}$$
(2)

$$\theta = \tan^{-1}(y/x), \ \theta \in [0,2\pi], \ j = \sqrt{-1}$$

Radial polynomial of ZMs is given by

$$R_{pq}^{Z}(x, y) = \sum_{s=0}^{(p-|q|)/2} \frac{(-1)^{s}(p-s)!(x^{2}+y^{2})^{\frac{p-2s}{2}}}{s!\left(\frac{p+|q|}{2}-s\right)!\left(\frac{p-|q|}{2}-s\right)!(\frac{p-|q|}{2}-s)!}$$
(3)

Zernike moments with negative values of repetition q are obtained directly by making use of the complex conjugate of Zernike moments for positive values. The angular functions in ZMs can be computed using recursion without making use of trigonometric functions which are computation extensive and the 8-way symmetry/anti-symmetry properties of the kernel functions further reduces the time computation by factor 8 approximately [9].

3. CLASSIFIERS (SIMILAR MEASURES)

Similarity measure scheme is quite significant to the recognition and retrieval results. In order to retrieve or recognize most similar images to query image, similarity functions are computed between the query image and database images, which is based on a set of feature vectors. The similarity measure takes advantage of the strengths of both global and local features for shape representation. Similarity measure is based on a distance measure. Given that each image is described by a feature vector representing its visual content description, distance and similarity computations are based on image feature vectors. Let x and y are two n-dimensional feature vectors of database image and query image, respectively, then the various similarity measures are defined as:

The Euclidean Distance (ED) is given by:

$$d_{ed}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

The *Squared Chord* (*SC*) is given by:

$$d_{sc}(x, y) = \sum_{i=1}^{n} \left(\sqrt{x_i} - \sqrt{y_i} \right)^2$$
(5)

(4)

The *Chi-Square Distance* (*CS*) is given by:

$$d_{cs}(x, y) = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{x_i + y_i}$$
(6)

The *Extended Canberra Distance (EC)* is given by:

$$d_{ec}(x, y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i + u_x| + |y_i + u_y|}$$
(7)

where
$$u_{x} = \sum_{i=1}^{N} x_{i} / n$$
 $u_{y} = \sum_{i=1}^{N} y_{i} / n$

The Cosine Measure Distance (CM) is given by:

$$d_{cm}(x, y) = \frac{\sum_{i=1}^{n} x_{i} y_{i}}{\left(\sqrt{\sum_{i=1}^{n} x_{i}^{2}} \sqrt{\sum_{i=1}^{n} y_{i}^{2}}\right)}$$

(8)

The *Paper Similarity Measure Distance (PSM)* is given by:

$$d_{ps}(x, y) = \left\| \frac{\sum_{i=1}^{n} \chi_{i} - \sum_{i=1}^{n} y_{i}}{1 + \sum_{i=1}^{n} \chi_{i} + \sum_{i=1}^{n} y_{i}} \right\|$$
(9)

The *Histogram Intersection Distance (HI)* is given by:

$$d_{hi}(x, y) = 1 - \frac{\sum_{i=1}^{n} \min(x_i, y_i)}{\sum_{i=1}^{n} \max(x_i, y_i)}$$
(10)

4. EXPERIMENTAL ANALYSIS

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the most common type of dementia among older people. An established risk factor for AD is mild cognitive impairment (MCI) which is described as a transitional state between normal aging and AD patients. MR images that we downloaded from ADNI were pre-processed. We considered 1 slice of all MR images in axial view and ZMs were calculated as features for each MRI. An experimental study was conducted on the 1 slice of 210 ADNI MRI databases, which includes 70 AD patients, 70 MCI subjects, and 70 HCs. We chose 50 percent of images (105 images) at random and used them in the training set (35 AD, 35 MCI and 35 HC) and rest 50 percent of images used as testing set. Table 1(a) represents the classification of AD vs. HC images using ZMs with different classifiers at different orders (order 5, 10 & 15) and from these details it is observed that the best results are obtained for

IJSER © 2017 http://www.ijser.org AD/HC at order 15 with cosine measure as classifier (accuracy 87.143%). Table 2(a) represents the classification of MCI vs. HC images using ZMs with different classifiers at different orders (order 5, 10 & 15) and the best results were obtained for HC/MCI at order 15 with cosine measure as classifier (accuracy 81.429%). The accuracy of AD/HC and HC/MCI with ZMs on different classifiers at different orders (order 5, 10 & 15) are plotted in figures 1(b) & 2(b).

Table 1(a): Classification of AD vs. HC images using

ZMs at order 5, 10 &15

Class ificati on Meth od and Train ing Algor ithm	Co sin e Me asu re	Pap er Sim ilari ty Me asur e	Euc lide an Dist anc e	Sq uar e Ch or d	Ch i Sq uar e	Hist ogra m Inter secti on	Ext end ed Ca nbe rra
ZMs (Orde	62. 857	52.8 57%	61.4 29%	55. 714	55. 714	51.42 9%	52.8 57
r 05)	%	57 /0	2770	%	%	270	%
ZMs	82.	64.2	68.5	75.	77.	68.57	68.5
(Orde	857	86%	71%	714	143	1%	71
r 10)	%			%	%		%
ZMs	87.	71.4	80%	80	78.	75.71	74.2
(Orde	143	29%		%	572	4%	86
r 15)	%				%		%

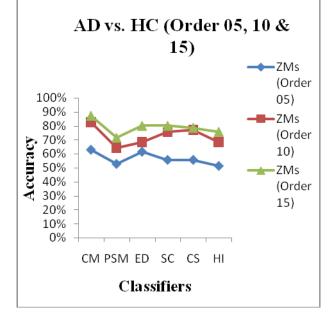
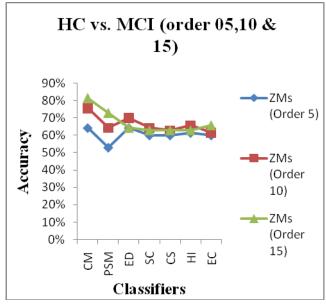
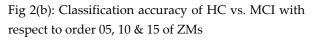


Fig 1(b): Classification accuracy of AD vs. HC with respect to order 05, 10 & 15 of ZMs

Table 2(a): Classification of HC vs. MCI images using ZMs at order 5, 10 &15

Class ificati on Meth od and Train ing Algor ithm	Co sin e Me asu re	Pap er Sim ilari ty Me asur e	Euc lide an Dist anc e	Sq uar e Ch or d	Ch i Sq uar e	Hist ogra m Inter secti on	Ext end ed Ca nbe rra
ZMs (Orde	64. 286	52.8 57%	64.2 86%	60 %	60 %	61.42 9%	60 %
r 05)	%						
ZMs	75.	64.2	70%	64.	62.	65.71	61.4
(Orde	714	86%		286	857	4%	29
r 10)	%			%	%		%
ZMs	81.	72.8	64.2	62.	62.	62.85	65.7
(Orde	429	57%	86%	857	857	7%	14
r 15)	%			%	%		%





5. CONCLUSION

A fast and recursive method of calculating ZMs was used in this paper for extracting discriminative information from structural MRI with the aim of the diagnosis of AD and classification between patients with AD, patients with MCI, and HC subjects. The results on ADNI MRI data for 210 subjects showed that our feature extraction and classification methods achieved good accuracy for the AD and MCI groups as well as the HC group. We have selected 50% (105 images) of the MRIs randomly for use in training classifiers and rest 50% (105 images) for the testing phase. The technique used here yielded the best overall classification results between AD and MCI using ZMs with cosine measure at order 15 (accuracy 87.143%) and for pairs of the MCI and HC using ZMs with cosine measure at order 15 (accuracy 81.429%). These results demonstrate the good precision and reliability of our method and provide a good choice for the diagnosis of AD.

6. REFRENCES

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