Universe Scientific Publishing

ORIGINAL ARTICLE

# A Computational Model of Quantitatively Measuring the Alzheimer's Disease Progression in Face Identification

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***Abstract:*** There are numerous large-scale biomedical and pharmacological research projects to study Alzheimer's Disease (AD), and potential drugs and therapeutic interventions to improve this severe disease. Of significant importance are life quality of AD patients. In particular, AD patient's ability to recognize intimate family members and nurses' faces largely decides their life quality. The broad objective of this research is focused on providing methods to determine the extent of disease progress from the viewpoint of recovering as much cognitive ability as possible. Specifically, this research would computerize the AD patient's diseased brain and retrained the brain with focus on recovering the visual recognition ability of family member and medical care personnel. Likewise, potential recommendations for the patients' family members and others who interact with the patients, in order to help improve quality of life and daily interactions.

***Keywords:*** Computational Model; Alzheimer's Disease; Face Identification

## 1. Introduction

Alzheimer's disease (AD) is one of the most prevalent degenerative disease of brain, caused by complex changes in brain with damaged neuron (Alzheimer's Association). Severe AD could lead to dementia, having difficulty in remembering things. While the irresistible fact of aging has been proven to be the greatest risk factor causing AD, this disease become a nonnegligible problem for everyone. AD is a progressive disease and is generally divided into three stages: mild (early stage), moderate (middle stage), severe (late stage). During the late stage, AD patients are unable to respond to environment and finally control movement. Cognitive skills and memory system are continuously deteriorating, so forgetting familiar faces and failing to identify families are common in this stage. Dementia and amnesia symptoms are common and severe for severe AD patients.

Despite years of devotion into AD field, there is still no way to prevent progression or a cure for the disease. A research on therapies for AD by Fluidic Analytics reveals that only 4 out of 146 drugs are effecting in treating AD since 1998. The estimated cost in 2015 to society is about $818 billion, including caring AD patients and devotion to AD research. More astonishingly, the global population of AD patients would increase up to 135 million by 2050, since the aging population also increase rapidly (Fluidic Analytics 2019).

Although numerous researchers have approached to improve Alzheimer's disease, a family tragedy and a social dilemma, no healing for AD have been discovered and the life quality of AD patient remain hard. Quality of life (QQL) is a well-established measurement for AD patient's life quality, including cognitive functioning, ability to perform daily living, ability to engage in activities, and a balance between positive and negative emotion (Lawton MP 1994).

Most researches related to Alzheimer's disease are


doi: 10.18686/esta.v6i1.93

seeking for an early diagnosis. They hope to discover potential AD patients as early as possible. Liu. & Liu & Cai [2014] and Ding.etc. [2018] offer two different model of classifying and pre-diagnosing AD based on technique of deep learning and convolutional network.

This work is motivated by the rapidly growing population of AD patients, the severe life qualities patients and their families are suffering, and the lack of practical research on how to efficiently improve patients' life quality.

# 2. Body

Face perception is the term referring to how human brain recognize and interpret faces and is also one of the most pinnacled inverse problem. Numerous neuropsychological experiments had revealed that human brain works the same as a gigantic neural network. Some recent studies utilizing deep learning are approaching to building the network. However, up to today, still no reliable researches are qualified to be an authoritative and comprehensive computational model of this abstruse memory system in human brain. To solve practical problems related to decipher the face perception, some researchers categorize it into 6 components based on many studies of face recognition (Leopold & Rhodes 2010). Identity, emotional expression, eye appearance(gaze), attraction, development and neural specialization constitute this cognitive process of gaining multidimensional information from face. Over the last few decades, countless researches have studied different parts of face recognition, and many profound algorithms and computational models have proliferated. Around the end of 20 century, active shape models (ASM) are invented and provide a very forerunner technique for face recognition in detecting facial features (Cootes 1995). ASM offers an alternative way of describing face images. Less than 10 years later, a significant framework is designed with a new image representation, the "Integral Image". It greatly improved the efficiency and the accuracy of face detection and promoted the application of face recognition (VIOLA & JONES 2004).

Limited to current capability to model face perception and considering our goal to ameliorate AD patients' life condition, we choose to build a computational model simulating how AD patients recognize faces and distinguish their identities.

We take the famous model by Turk and Pentland [1991] in which eigenfaces are applied to be a linear combination of facial features. Following the paper and Sirovich and Kirby [1987] which shared a similar idea using 'eigenpicture' , the steps of building our model could be separated into two parts:

## 2.1 Computing the eigenfaces (part 1)

Step 1: Collect set of size $n$ face images of the AD patient's family members and medical personnel be the training set. Similar background, such as white wall, and similar size of centered faces in picture is preferred due to the limitation of this model.

Step 2: Represent each image as a vector consisting of $128 \times 128 = 16384$ pixels. Thus, a $16384 \times n$ matrix L is created.

Step 3: Normalize the matrix L by subtracting the average face from each face, which is the collection of 'caricatures' defined by Sirovich and Kirby.

Step 4: Find the eigenvector and eigenvalues of the covariance matrix $L' = LL^T$.

Step 5: Choose M eigenvectors, namely principal components, with the highest associated Eigenvalues. The M images is the 'face space'. Each face in the training set is a projection of its caricature onto the M-dimensional 'face space' with the average face, and also is a linear combination of the principal components.

## 2.2 Recognize faces (part 2)

Step 1: Normalize the new face and project them onto the 'face space'.

Step 2: Choose a threshold $\theta_e$ defining the maximum allowable distance from face class and calculating the distance $e_i$ between the new face and the face class. Compare the threshold and the calculated distance. Among the methods of evaluating distance, common Euclidean distance is easy and simple; Mahanlanobis distance and angle-based distance perform the best in recognition process (Perlibakas 2003).

Step 4: If $e_i < \theta_e$, this new face should be recognized as a family member or nurses of this AD Patient. The face should be added into the face class and the face space would be recomputed, which are steps for constantly learning model.

Slightly modifying Turk and Pentland's model, we have a primary computational model about how AD patients could correctly recognize faces of their intimate relatives and medical staff. This model is simple, efficient and accurate for face recognition, which had been verified by experiments done by Turk and Pentland. Though, as raised in the paper, compared to some latest model for face recognition, this model is only effective in a constrained environment (small set). Under our case, this model provides a very practical and efficient solution.

Because AD patients meet the most problem in getting to forget or being confounding about who are their acquaintances, the treatment should merely help them recognize the identity of their intimate family members and some medical personnel from a large but unimportant population. Hence, the size of the set of valid faces is small, and the difficulty of recognition is not that high compared to other social dilemmas, such as criminal identification. In our case, we could reasonably require patients' families to present the most explicit image of face in front of them. While other popular models for face recognition may be more advanced, this eigenface model emphasizing significant features of faces best fits our situation.

## 2.3 Perturbation

To update the primary model for AD patients, we need to perturb some steps in the algorithm to simulate the brain with amnesia.

A well-confirmed statement is that AD patients' brain fails to do some required analysis of the image it received. AD patients at stage three have severe difficulty in focusing and concentrating. Hypothetically, AD patients' brain cannot differentiate between important and unimportant features from received information. Equivalently, under the approach of eigenfaces with taking M principal components, AD patients may miss the principal components containing the most information. The dysfunctional brain could incorrectly take another principal component as the most useful one. For example, three principal components contain 1%, 2%, and 97% of information of faces, and the brain consider the first two components most important. Besides, the brain could fail to include as many components as needed. For example, four principal components contain 25% each, and the brain is only able to have maximum two components with only 50% of information.

## 2.4 Perturb the model (part 3)

Step 1: Change the rule of picking eigenvectors (principal components) in Part 1 Step 5. (1) Randomly pick M eigenvectors of matrix $L^{'}$. (2) Pick $M/2$ eigenvectors with highest eigenvalues of matrix $L^{'}$. (3) Pick 2 eigenvectors with highest eigenvalue of matrix $L^{'}$ $(M = 2)$. Step 2: Repeat the other steps listed above. Step 3: Compare the accuracy of testing result on new faces.

After the three-parts steps, we have the computational model for AD patients having difficulty in recognizing faces. The accuracy of this computational model could be easily verified, since the only change of this AD model from the Eigenface model by Turk and Pentland is the rule of selecting principal components. Nonetheless, the reliability of this AD model in biological field require further some experiments to support that real AD patients perform the same as the AD model when recognizing specific identities of faces. One suggestive experiment might apply the visual mismatch negativity (vMNN) which is a component of N2 visual even-related potential (ERP) and is observed by researchers displaying abnormal increase over a specific measurement epoch (Tales 2008).

Quantitative Measurement/Recovering:

Now we have a simple and valid model as we needed. To transform the model compatible for quantitatively measuring the extent of disease progress from the perspective of recovering cognitive ability, we need to consider some clinical practices which have been verified by pharmacological experiment. Eye-contact training had proved to be one qualified and popular treatment against Alzheimer's disease. A recent study testing eye contact effect on face identification for AD patients, aging people and young adults claims that the eye contact effect decreases as elder age. It provides robust behavioral evidence supporting that for AD patients, performance of recognizing faces could be improved by taking 'direct-gaze' effect, equivalently the eye-contact training in clinical treatment (Lopis 2019). Another neuroscientific research through functional resonance imaging (fMRI) illustrates that AD and mild cognitive impaired (MCI) patients have an impairment in inhibitory control of saccadic eye-movement, which is a rapid special eye-movement pattern (Alichniewicz, Brunner, Klünemann, & Greenlee, 2013). It implied that the patients' brain have function deficit in controlling eye-movement, which directly correlates to face identification. AD patients' eye-movement is more likely to locate around nose rather than eye (Firestone 2007). We modify the model to compulsively extract most eye-central information from images.

### 2.5 Recover the model using eye-contact training (part 4)

Step 1: Locate eigenvectors telling the most eye-central information. Since the size of our image set is small, the maximum number of eigenvectors is also small. We could examine each eigenvector orderly to have the eye related information. The method of examination would evolve technique to recognize 'eye' from images and active shape model is a good choice.

Step 2: Choose the selected eigenvectors and finish the process of eye-contact training.

Step 3: Repeat the following steps and get the results.

By computerizing the eye-movement treatment and adding it into the AD model, we have a qualified computational model that could predict the theoretical extent of disease progression and the numeric result of the model is the quantitative scoring for the treatment's recovering effect.

## 3. Discussion

Our computational model simulating how AD patients recognize faces and how much disease would progress after applying a clinical treatment. The overall methods are built on the basis of other's successful researching result and theoretical validation. Further development need to validate and update this primary model and be more comprehensive and exhaustive. Some complex details of AD patients are ignored in this project, such that the disease could be categorized into seven stages, while one therapy might perform diversely on different stages. Also, the method of locating eye-central pictures require more attention.

On another side, this model presents an innovative view of solving AD and amnesia problems. It does validly reveal the possibility of analyzing and solving the AD patients' amnesia problem, tightly relating to mild cognitive impaired patients (MCI) and memory-system impaired robots. Moreover, it does provide a simple, effective and practical approach to this problem from the viewpoint of face recognition on identity instead of face perception. It focuses on modelling how eye-movement training could help prevent the Alzheimer's disease progression. In application, with respect to an AD patient or another cognitive impaired patient with similar diagnosis, doctors or families are able to more directly understand to what extent an insignificant dysfunction in brain effect the patient's ability of recognition, and to what extent a specific therapy would benefit the patient. With enough further researches on this topic, each patient is able to have their unique disease model. Besides, the corresponding physician could forecast and compare the curative effect of different therapies through using the updated model. The model could also be a useful approach for validating a new-coming drug or non-drug treatment.

This new practical viewpoint is an accessible, efficient and beneficial way of considering Alzheimer's disease and amnesia, especially compared with arduous topic on face perception and memory-system modelling. This computational model applies directly on improve Alzheimer's disease patients' life quality in face identification. It could not only facilitate physician but also encourage families.

## Acknowledgement

Professor Assadi

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