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FACE RECOGNITION IN NEUROSCIENCE: A REMEDY FOR PROSOPAGNOSIA AFFECTED PEOPLE

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FACE RECOGNITION IN NEUROSCIENCE: A REMEDY FOR PROSOPAGNOSIA AFFECTED PEOPLE

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Abstract - Face recognition is one of the most relevant applications of image analysis. It's a true challenge to build an automated system which equals human ability to recognize faces. In the topic presented below the focus is on application of face recognition in Neuroscience, to help people affected with Prosopagnosia. Prosopagnosia is a disorder of face perception where the ability of a patient to recognize faces is impaired, while the ability to recognize other objects may be relatively intact.There are many algorithms proposed for face recognition. The most successful approach of those are the extensions of the principal component analysis.

***Keywords**--Prosopagnosia,eigenface, face recognition, principal component analysis,matlab, adaboost algorithm, Haar Filter.*

I. INTRODUCTION

Information and Communication Technology is increasingly making a foray into all aspects of our life regardless of sectors. Its opening a world of unprecedented scenarios and possibilities where people interact with electronic devices embedded in their environments that are sensitive and responsive to the presence of users. Although humans are quite good identifying known faces, we are not very skilled when we must deal with a large number of unfamiliar faces. Computers, with an almost limitless memory and computational speed, should overcome the limitations of a human being. Face recognition imbibes multiple technology solutions in the likes of pattern recognition, neural networks[3], computer graphics, image processing etc...

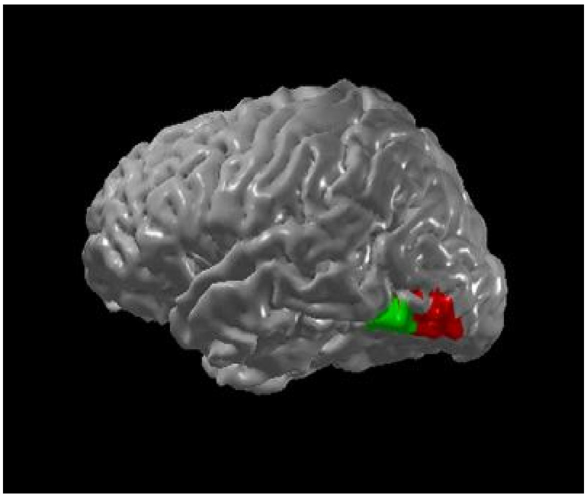

Fig.1 Location of Fusiform gyrus

II. PROSOPAGNOSIA

Prosopagnosia is a neurological disorder characterized by the inability to recognize faces. Prosopagnosia is also known as face blindness or facial agnosia. Previous studies have shown that the lesions producing the disorder can occur in diverse areas of the brain. Depending upon the degree of impairment, some people with prosopagnosia may only have difficulty recognizing a familiar face; others will be unable to discriminate between unknown faces, while still others may not even be able to distinguish a face as being different from an object.

Some people with the disorder are unable to recognize their own face. Prosopagnosia is not related to memory dysfunction, memory loss, impaired vision, or learning disabilities.

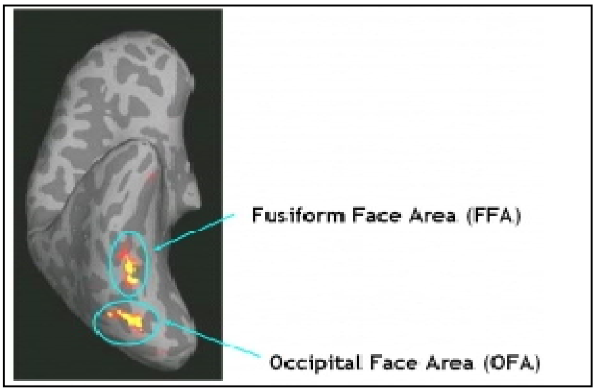

Fig.2 Fusiform area.

Prosopagnosia is thought to be the result of abnormalities, damage, or impairment in the right fusiform gyrus(*Refer fig:1*), a fold in the brain that appears to coordinate the neural systems that control facial perception and memory. Prosopagnosia can result from stroke, traumatic brain injury, or certain neurodegenerative diseases

III. ON LINEF ACERECOGNITION ALGORITHM

Proposed System:

A new online boosting algorithm is introduced: a face recognition method that extends a boosting-based classifier by adding new classes while avoiding the need of retraining the classifier each time a new person joins the system. The classifier is learned using multitask learning principle where multiple verification tasks are trained together sharing the same feature space. The new classes are added by taking advantage of the structure learned previously, being the addition of new classes not computationally demanding. The present proposal is going to validated with different facial data sets by comparing this approach with the current state-of-the-art techniques.

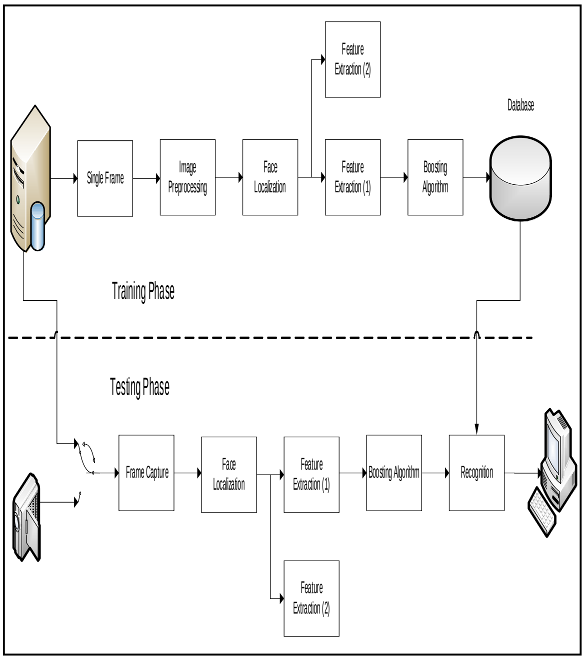

Fig.3 Top level Block Diagram

Phase one of implementation of the system would be to collect a wide variety of facial images. Collecting standard pictures of co-operative friends and family members lead to a suitable sample collection. Each person was photographed at various angles to provide different perspectives of the same facial image. Each of the pictures is tagged with the respective person's credentials in the data base. During the execution of the application if any one of the subjects who have an image in the data base appears in front of the camera the applications instantly recognizes the individual and pulls up the contacts and other details of the individual. The information displayed on the screen can help the patient in recognizing the individual.It can be shown in *Figure 4.*

Fig.4 Application in neuroscience

IV. FACE DETECTION

Recently, a powerful face detection method based on AdaBoost algorithm is drawing attention to various applications. This method provides face detection systems with a good detection rate, although a considerable number of weak classifiers are needed.

Face Detection based on Haar-like features andAdaBoost algorithm:

This technique relies on the use of simple Haar-like features with a new image representation (integral image). TheAdaBoost is used to select the most prominentfeatures among a large number of extracted features. Finally, a strong classifier fromboosting a set of weak classifiers would be extracted. This approach has proven tobe an effective algorithm to visual object detection and also one of the first real-time frontal-view face detectors.

The effectiveness of this approach is based on some particular facts.

1. Using a set of simple masks similar to Haar-filters.
2. Using integral image representation which speeds up the feature extraction.
3. Using a learning algorithm, AdaBoost, yielding an effective classifier, whichdecreases the number of features.
4. Using the Attentional Cascade structure which allows background region of animage to be quickly discarded while spending more computation on promisingobject-like regions.

Haar-like features: Feature extraction

Working with only image intensities (*i.e.* the greylevel pixel values at each andevery pixel of image) generally makes the task computationally expensive. An alternate feature set to the usual image intensities can be much faster. This featureset considers rectangular regions of the image and sums up the pixels in this region.Additionally, features carry better domain knowledge than pixels. The feature value is defined as the difference value between the sumof the luminance of some region(*s)* pixels and the sum of the luminance of otherregion(*s*) pixels. The position and the size of the features depend on the detectionbox.

V. PCA BASED EIGENFACE ALGORITHM

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. A set of eigenfaces can be generated by performing a mathematical process called principal component analysis (PCA)[1] on a large set of images depicting different human faces. Informally, eigenfaces can be considered a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces.

Practical implementation

To create a set of Eigen faces,

(i)Prepare a training set offace images. The pictures constituting the training set should have been taken under the same lighting conditions, and must be normalized to have the eyes and mouths aligned across all images. They must also be all resampled to a common pixel resolution ($r \times c$). Each image is treated as one vector, simply by concatenating the rows of pixels in the original image, resulting in a single row with $r \times c$ elements. For this implementation, it is assumed that all images of the training set are stored in a single matrixT, where each row of the matrix is an image.

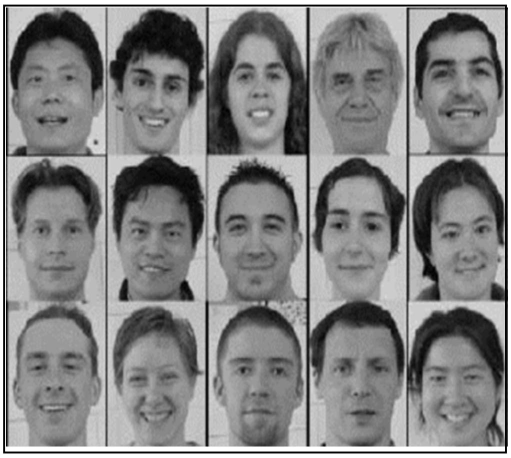

Fig.4 Training set of images

(ii)Subtract the mean. The average image a has to be calculated and then subtracted from each original image in T.

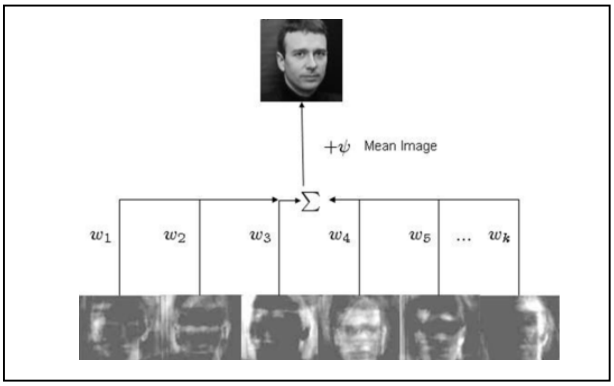

Fig.5 Mean and average of pixels on face

(iii)Calculate the eigenvectors and eigenvalues[2] of the covariance matrixS. Each eigenvector has the same dimensionality (number of components) as the original images, and thus can itself be seen as an image. The eigenvectors of this covariance matrix are therefore called eigenfaces. They are the directions in which the images differ from the mean image. Usually this will be a computationally expensive step (if at all possible), but the practical applicability of eigenfaces stems from the possibility to compute the eigenvectors of S efficiently, without ever computing S explicitly, as detailed below.

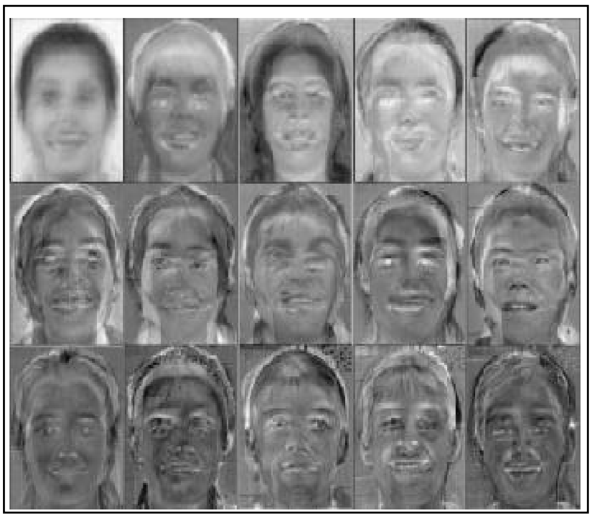

Fig. 5 Corresponding eigen faces of training set of images.

(iv) Choose the principal components. The D x D covariance matrix will result in D eigenvectors, each representing a direction in the $r \times c$-dimensional image space. The eigenvectors (eigenfaces) with largest associated eigenvalue are kept as eigenspace.

These eigenfaces can now be used to represent both existing and new faces: we can project a new (mean-subtracted) image on the eigenfaces and thereby record how that new face differs from the mean face. The eigenvalues associated with each eigenface represent how much the images in the training set vary from the mean image in that direction. We lose information by projecting the image on a subset of the eigenvectors, but we minimize this loss by keeping those eigenfaces with the largest eigenvalues. For instance, if we are working with a 100 x 100 image, then we will obtain 10,000 eigenvectors. In practical applications, most faces can typically be identified using a projection on between 100 and 150 eigenfaces, so that most of the 10,000 eigenvectors can be discarded.

Computing the eigenvectors

Performing PCA directly on the covariance matrix of the images is often computationally infeasible. The rank of the covariance matrix is limited by the number of training examples: if there are *N* training examples, there will be at most *N-1* eigenvectors with non-zero eigenvalues. If the number of training examples is smaller than the dimensionality of the images, the principal components can be computed more easily as follows.

Let T be the matrix of preprocessed training examples, where each column contains one mean-subtracted image. The covariance matrix can then be computed as $S = TT^T$ and the eigenvector decomposition of**S** is given by

$$\mathbf{S}\mathbf{v}_i = \mathbf{T}\mathbf{T}^T\mathbf{v}_i = \lambda_i \mathbf{v}_i$$

However TT^T is a large matrix, take the eigenvalue decomposition of

$$\mathbf{T}^T\mathbf{T}\mathbf{u}_i = \lambda_i \mathbf{u}_i$$

then we notice that by pre-multiplying both sides of the equation with T, we obtain

$$\mathbf{T}\mathbf{T}^T\mathbf{T}\mathbf{u}_i = \lambda_i \mathbf{T}\mathbf{u}_i$$

Meaning that, if u_i is an eigenvector of T^TT, then $v_i=Tu_i$ is an eigenvector of S.

VI. CONCLUSION AND FUTURE WORK

Face recognition is rapidly developing area with many possible applications which includes crowd surveillance to human-computer interaction. The goal of this project is to develop a real time face recognition system for people who suffer from ‘face blind’, where the application of face recognition in the area of neuroscience might be of paramount importance.

There are different algorithms available to perform face recognition. Here algorithms were developed for each component and their performance was evaluated in real time environment. It is concluded that Eigenfaces is an excellent basis for face recognition system, providing high recognition accuracy and moderate insensitivity to lightning variations. Eigenfaces are sensitive to scale reductions of less than 88% and rotations of more than 10 degrees.

The solution proposed above can be of great significance to a patient suffering from “face blind”. A portable device with an on board camera can be used by the patient to take pictures of individuals who he/she encounters in the real world. (Provided that familiar people to the patient is expected to have their credentials in the database). The application on the portable device can then pull up the information of the individual from the database. This can inspire the individual to be confident to lead a normal life in the real world.

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