Study of Automated Face Recognition System for Office Door Access Control Application

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Abstract— **The security currently become a very important issue in public or private institutions in which various security systems have been proposed and developed for some crucial processes such as person identifications, verification or recognition especially for building access control, suspect identifications by the police, driver licenses and many others. Face recognitions have been an active area of research with numerous applications since late 1980s and become one of the important elements in security system development. This paper focuses on the study and development on an automated face recognition system with the potential application for office door access control. The technique of eigenfaces based on the principle component analysis (PCA) and artificial neural networks have been applied into the system. The study includes the analysis of the influences of three main factors of face recognition namely illumination, distance and subject's head orientation on the developed face recognition system purposely built for office door access control. The experimental results have shown that the developed system has achieved good performance of face recognition rate of 80% at the distance of camera and subject between 40 cm to 60 cm and the subject's orientation head angle must be within the range of -20 to +20 degrees.**

Keywords: Face Recognition, Neural Network, Eigenface, Principal Component Analysis, Door access

I. INTRODUCTION

Face recognition (FR) has received significant attention during the last two decades and many researchers study various aspects of it [6]. The reasons for that could be that we try to explore the wide range of commercial and security application and the second is the availability of feasible computer technology to develop and implement application that require high computational power. In fact, FR has become an important issue in many applications such as access control, security systems, credit card verification and criminal identification. For example, the ability to model a particular face and distinguish it from other face images models would make it possible to improve one person identification or recognition. However FR system alone has limitation because it requires very cooperative subjects to put their faces in front of the system. Actually, the ability to detect faces at the first place, as opposed to recognizing them, can be very important. This is due to the fact the process of face detection is considered the first step in an automated face recognition system. Without detected face region, face recognition would not be possible. Otherwise, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. The first step of human face identification is to extract the relevant features from facial images. The question naturally arises as to how well facial features can be quantized. If such a quantization if possible then a computer should be capable of recognizing a face given a set of features. There are three major research groups which propose three different approaches to the face recognition problem. The largest group has dealt with facial characteristics which are used by human beings in recognizing individual faces. The second group performs human face identification based on feature vectors extracted from profile silhouettes while the third group uses feature vectors extracted from a frontal view of the face [1]. Most of face recognition algorithms fall into one of two main approaches: feature-based and image-based algorithms. Feature-based methods explore a set of geometric features, such as the distance between the eyes or the size of the eyes, and use these measures to represent the given face. These features are computed using simple correlation filters with expected templates. These methods are somewhat invariant to changes in illumination and can partially compensate for changes in camera location. However, they are sensitive to aging and facial expressions. It is also not clear which features are important for classification, an area in which more mathematical studies are needed. There are fundamental mathematical results in the literature that try to address these questions and have not yet been fully exploited for face recognition [2]. In this paper, an automated face recognition system application is designed for the purpose of door access control application. The FR system developed is based on the well known Eigenface technique which is derived from Principle Component Analysis (PCA).

II. PRINCIPLE COMPONENTS ANALYSIS FOR FACE RECOGNITION

The popular technique in FR for feature selection and dimensionality reduction is Principle Component Analysis (PCA). This techniques has been used in [3][4][5]. PCA is a

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standard de-correlation technique and following its application, one derives an orthogonal projection basis which directly leads to dimensionality reduction, and possibly to feature selection. Let $X \epsilon \mathbb{R}^N$ be a random vector representing an image, where *N* is the dimensionality of the image space. The vector is formed by concatenating the rows or the columns of the image which may be normalized to have a unit norm. The covariance matrix of *X* is defined as follows:

$$\Sigma_X = E\{[X - E(X)][X - E(X)]^t\}, \quad (1)$$

Where $E(.)$ is the expectation operator, t denotes the transpose operation, and $\Sigma_X \epsilon \mathbb{R}^{NxN}$. The PCA of a random vector X factorizes the covariance matrix Σ_X into the following form:

$$\Sigma_X = \Phi\Lambda\Phi^t \; with \; \Phi = [\phi_1\phi_2 \cdots \phi_N] \quad , \quad \Lambda = diag\{\lambda_1, \lambda_2, \cdots, \lambda_N\}, \quad (2)$$

Where $\Phi \epsilon \mathbb{R}^{NxN}$ is an orthonormal eigenvector matrix and $\Lambda \epsilon \mathbb{R}^{NxN}$, a diagonal eigenvalue matrix with diagonal elements in decreasing order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N$, $\phi_1, \phi_2, \cdots, \phi_N$ and $\lambda_1, \lambda_2, \cdots, \lambda_N$ are the eigenvectors and the eigenvalues of Σ_X respectively.

An important property of PCA is de-correlation, that is, the components of the transformation, $X' = \Phi^t X$, are de-correlated since the covariance matrix of *X'* is diagonal, $\Sigma_{X'} = \Lambda$, and the diagonal elements are the variances of the corresponding components. Another property of PCA is its optimal signal reconstruction in the sense of minimum Mean Square Error (MSE) when only a subset of principal components where $P = [\phi_1\phi_2 \cdots \phi_m]$, $m < N$, and $P \epsilon \mathbb{R}^{Nxm}$ are used to represent the original signal. Following this property, an immediate application of PCA is the dimensionality reduction:

$$Y = P^t X \quad (3)$$

The lower-dimensional vector $Y \epsilon \mathbb{R}^m$ captures the most expressive features of the original data *X*. As PCA derives projection axes based on the observed variations using all the training samples, it enjoys good generalization abilities for image reconstruction when tested with novel images not seen during training. The disadvantage of PCA is that it does not distinguish the different roles of the within and the between class variations and it treats them equally. This should lead to poor testing performance when the distributions of the face classes are not separated by the mean-difference but, instead, by the covariance-difference. High variance by itself does not necessarily lead to good discrimination ability unless the corresponding distribution is multimodal and the modes correspond to the classes to be discriminated. One should also be aware that as PCA encodes only for second order statistics, it lacks phase and, thus, locality information. Based on the technique of PCA, Turk and Pentland in [4] have successfully developed a well-known nearly real time face recognition system, known as Eigenfaces, where the eigenfaces correspond to the eigenvectors associated with the dominant eigenvalues of the face covariance matrix. The eigenfaces define a feature space, or "face space," which drastically reduces the dimensionality of the original space, and face detection and identification are carried out in the reduced space.

III. METHODOLOGY AND SYSTEM DEVELOPMENT

The development of this automated face recognition system is done in typical face recognition's two stages which are training stage and evaluation stage. In the first stage, the specific number of training image of face candidate is captured. The features are extracted from the intensity image of human frontal faces using principle component analysis. The system will then learn on the extracted features and store them in its database. In the second stage, the system will recognize new faces in an unsupervised manner and that is easy to implement using artificial neural network. The generic framework of the system is shown in Figure 1.

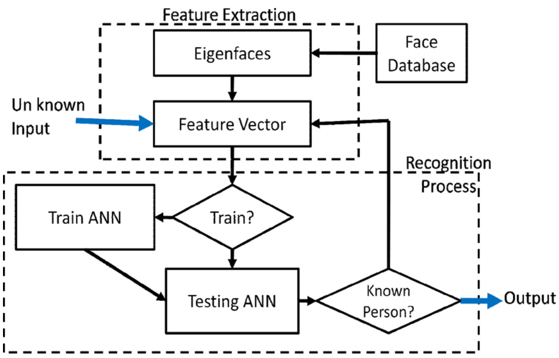

Figure 1: Generic Framework of FR system

The development of Graphical User Interface (GUI) and the application of Artificial Neural Networks in the system have been done by using Microsoft Visual C++ and Visual Basic 2008 platforms. Two type of face databases were used to train the system. The first type consists of captured and cropped face images of persons to be recognized. There are ten images for each person where the variations of frontal face positions are twenty degrees rotation to left and right directions perpendicular to the camera. These images are captured in advance using camera, cropped and then are trained into the system and kept inside system's face database. Meanwhile, the second face database consists of the ad-hoc face frontal images that are captured instantly using the system's camera. The number and the characteristics of these captured images are similar to the first type of face databases. The number of face training images can be increased later to observe the performance of FR system. Actually, the creation of the second type of face database has an advantage where the action can be done online. Figure 2 show the GUI snapshot of FR system.

Figure 2: Interface of the system

IV. Experimental Frameworks And Results

In this project, the application of face recognition has been studied in order to investigate the suitability of designing an automated face recognition system for door access control. The experimental works focused only on studying the effect of illumination, distance of subject's face and the angle of rotation of the subject's face. Illumination is considered as major factor that influence the performance of any face recognition system. In our experiment, the intensity of illumination has been varied and digital lux light meter has been used to measure this intensity variation. The measurement is in lux and the source of the light is located at the camera of FR system itself. In the second factor which is the distance of subject, usual measurement unit in centimetre has been used. This measurement represents the distance from FR camera to the frontal face of the subject. With these two factors, it is logic to assume that the larger the distance, the smaller the intensity obtained. Therefore, the first experiment was done to investigate their relation and the result is shown in Figure 3. In this figure, the assumption made was justified where the farther the distance, the lower the value of light intensity.

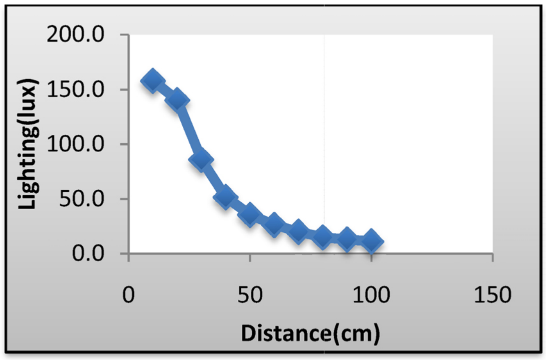

Figure 3: Relation between illumination and distance

The third factor that had been considered in this paper is the orientation angle of a subject's face toward the system's camera. By assuming the perpendicular distance from the camera and the frontal face subject as zero degree, any head rotation to the right direction of the face is considered positive angle while head rotation to the left direction is considered negative angle. The illustration of this experiment is shown in Figure 4.

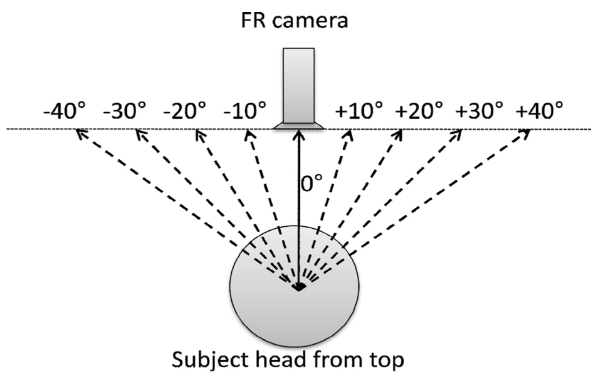

Figure 4: Illustration of orientation position of subject's head

With the three factors under consideration, the system has been tested with five different individuals where their frontal face images have been captured and stored in the face database. The first two individuals face database has been created using the first face database type and the other three individuals face database has been created using the second face database type. The tests have been performed with the variation of subject's distance and its head rotational angle. The results obtained are shown in Table 1.

Table 1: Overall performance of recognition of the system when tested with the variation of distance of the face and subject's rotational head position with respect to the camera. 'x' indicate that face is recognized while '-' represent unknown face.

Distance (cm)	Angle (degree) -40	-30	-20	-10	0	+10	+20	+30	+40	Recognition rate	%
10	-	-	-	-	-	-	-	-	-	0/9	0.0
20	-	-	-	x	x	x	-	-	-	3/9	33.3
30	-	-	-	x	x	x	-	-	-	3/9	33.3
40	-	x	x	x	x	x	x	x	-	7/9	77.7
50	-	-	x	x	x	x	x	-	-	5/9	55.5
60	-	-	x	x	x	x	x	-	-	5/9	55.5
70	-	-	-	x	x	x	x	-	-	4/9	44.4
80	-	-	-	x	x	x	-	-	-	3/9	33.3
90	-	-	-	x	x	x	-	-	-	3/9	33.3
100	-	-	-	-	x	-	-	-	-	1/9	11.1

From the results obtained, the developed automated face recognition system has been able to recognize nearly 78% of different orientation position of the subject's face at 40 cm from the camera. However, the system has failed to perform face recognition when the distance of the subject's face is less than 10 cm. This is due to the fact that the face image is so close to the camera and the face region captured is not complete. For the subject's distance above 50 cm from the camera, the system's recognition performance rate has dropped from about 56% to 12%. It shows that the farther the distance, the smaller face image captured and lower lighting lux value. The highest recognition rate achieved by the system is obtained with the distance of camera and subject is between 40 cm to 60 cm. In this range, the recognition rate is reasonable, but the subject's rotational head angle must be within the range of -20 to +20 degrees only. When the rotational angle variation is more than -30 or +30 degrees, the system has failed. The system with user face recognition process is shown in Figure 5.

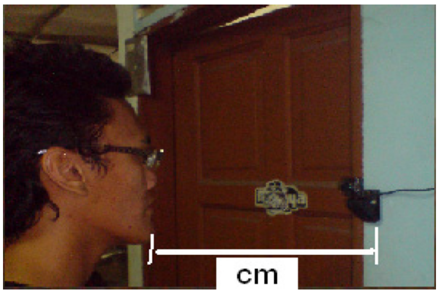

Figure 5: The camera of the system is capturing candidate's face image from a specific distance

V. Conclusions And Future Works

In this paper, an automated face recognition system has been developed in order to study the potential application for office door access control. The technique of eigenfaces based on the principle component analysis (PCA) and artificial neural networks have been applied into the system. The training images can be obtained either offline using in-advance captured and cropped face images or online using the system's face detection and recognition training modules on the real frontal face images. The system has been able to recognize face at reasonable rate at the distance between 40 cm to 60 cm from the camera with the subject's head rotational angle is between -20 to +20 degrees. The experimental results have also confirmed the influences of illumination and pose toward face recognition system. Finally, for a prototype development of office door access control system using face recognition, it is suggested that the system should be applied in the condition above in order to obtain the highest performance of the system. There are also potential researches that could be done to improve the performance of face recognition rate such as the increase number of training images, the characteristics of the lighting source, the background in front of the camera, the use of more robust algorithm etc.

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