

Developing the Age Dependent Face Recognition System

Hlaing Htake Khaung Tin, Myint Myint Sein

University of Computer Studies, Yangon, Myanmar

Corresponding authors' Email: hlainghtakekhaungtin@gmail.com; myintucsy@gmail.com

Abstract: This paper details with the developing of the age dependent face recognition system. The YC_bC_r and HSV colors spaces are applied to skin detection and face region extraction. The proposed method preserves the identity of the subject while enforcing a realistic recognition effect on adult facial images between 15 to 60 years old that are divided into 11 classes with 5 years old range. The age of the input individual is predicted to examine the related age group. Eigen face approach is applied to both the training data and each aging group of database. And, then the face recognition is performed with a predicted aging group. Based on the principal component analysis method and K^{th} nearest neighbor classifier, the face recognition system is developed. The proposed system will reduce the complexity and processing time dramatically by considering the dependent aging groups of an individual instead of the whole database.

Keywords: age prediction; face recognition; principal component analysis; geometric feature; age dependent face recognition

1. Introduction

Nowadays, as increasing security is being demanded in everywhere of the human society, so face recognition has become a very active in human biometrics research area. Numerous approaches of face recognition and considerable successes have been proposed [1-10]. However, it is still a difficult task to recognize the human faces accurately in real-time, especially under variable circumstances such as variations in illumination, pose, facial expression, makeup, etc. In face recognition, the similarity of human faces and the unpredictable variations are the greatest obstacles for a huge database. The age based face recognition system is developed to provide solution to these problems. The face database is divided in to 11 groups depending on age. Each aging group contains at least 20 face images. Both the face image and its personal record are included in each aging database group.

Age prediction is concerned with the use of a training set to train a model that can estimate the age of

the facial images. The age prediction is carried out by projecting a new face image into this face space and then comparing its position in the face space with that of known faces. The predicted age is applied to extract the related age class from database.

Aging is a source of variation which has only recently been gaining attention. Understanding the appearance variations induced by aging is important for applications where the claimed identity and enrolled face may show a large difference in apparent age. Studies in neuroscience have shown that facial geometry is a strong factor that influences age perception [1]. Determining the age of a person from a digital picture is an intriguing problem with many potential uses, from improving face recognition through gallery binning to auto indexing of digital pictures to automatic demographic generation [2].

Among the first researchers of age prediction, Kwon and Vitoria Lobo proposed a method to classify input face images into one of the following three age

groups: babies, young adults and senior adults [3]. Their study was based on geometric ratios and skin wrinkle analysis. Geometric ratios were first computed from facial features to distinguish babies from adults. The ratio of the distance between eyes and nose worked best for separating babies from adults. After that, seniors were distinguished from young adults and babies by detecting and measuring skin wrinkles using snakes. Then, a fusion rule was used to combine the ratios and wrinkle information to judge age category. Their method was tested on a database of only 47 high resolution face images containing babies, young and middle aged adults.

Hayashi et al. [4] focused their study on facial wrinkles for the estimation of age and gender. Skin regions were first extracted from the face images, followed histogram equalization to enhance wrinkles. Then, a special Hough transform, Digital Template Hough Transform was used to extract both the shorter and longer wrinkles on the face. Their experiments were not very successful on the age classification task though, achieving only 27% accuracy of age estimation and 83% on gender classification. It is important to note that they did not mention the size or source of their test to generate their accuracy values. Hayashi also noted the difficulty of extracting wrinkles from females' ages between 20 and 30 due to the presence of makeup.

Most of the researches in this area is very limited by the size and quality of the database used. Experimental results revealed that the area around the eyes proved to be the most significant for age prediction. Lanitis [5] empirically studied the significance of different facial parts for automatic age estimation. His study was limited to subject ranging from 0 to 35 years old, and contained 330 images, of which only 80 were used for testing purposes. Evidently, faces with more wrinkles weren't used, leaving in doubt his ability to estimate the age of subjects older than 35 years. He claims that introduction of the hairline (when using the whole face) has a negative effect on the results. The model of the upper facial part minimized estimation error and standard deviation resulting in a mean error of 3.83 years and a standard deviation of 3.70 years.

Some researchers have focused on particular age groups only, while others use an extremely wide classification range. Primarily, due to the lack of a good database, a global age prediction function, covering an extensive range of ages has yet to be developed. J. R. Sclar and P. Navarreto [6] proposed a face recognition algorithm

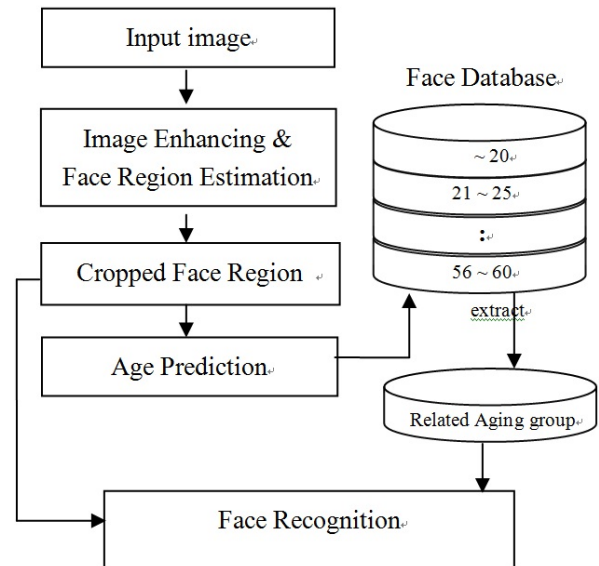


Figure 1 Illustration of the System Overview.

based on Eigen space. J. Yang et al. [7] introduced a new approach to appearance based face representation and recognition.

The robust face recognition system is proposed in this paper. The recognition is performed for the related aging group of predicted age. It will reduce the processing time and complexity than the finding of matched face in the whole database. Age prediction is concerned with the use of a training set to train a model that can estimate the age of the facial images. In age prediction process, Eigen method is applied to both the training data and each aging group of database. A face recognition algorithm is developed based on the principal component analysis method and KNN classifier. The proposed system will not only recognize the face of individual but also produce the record of the corresponding person.

2. System Overview

The input image can be obtained by taking a camera or a scanner. After image enhancing and skin color detection steps, the face region from a real image is extracted. The weight vectors of the cropped face feature are computed for age prediction. Face database is built by the eleven age individual groups of faces. The relative age group is selected by the predicted age of input individual. The overview of the proposed system is illustrated in Figure 1.

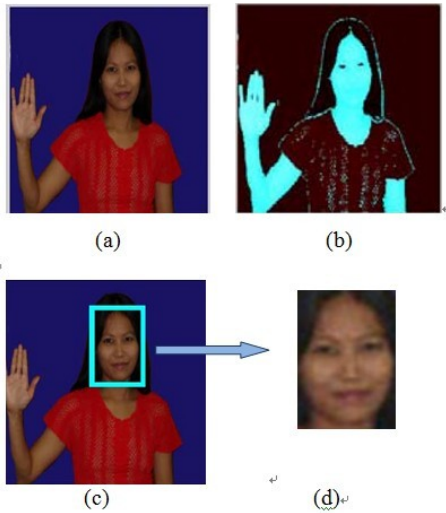


Figure 2 Face region Extraction: (a) Color image (b) Skin detection and (c) Detected face region (d) Resized face image.

3. Face Region Extraction

To provide the building of database and face recognition, face region extraction has been done based on the skin detection approach. Most existing skin segmentation techniques involve the classification of individual image pixels into skin and non-skin categories on the basis of pixel color. For extracting the face region, three colors spaces, RGB , YC_bC_r and HSV color space are applied for skin detection after de-noising. One important factor that should be considered to detect skin colored regions becomes robust only if chrominance component is used in analysis. Therefore, the variation of luminance component is eliminated as much as possible by choosing the C_bC_r plane (chrominance) of the YC_bC_r color space to build the model. The skin color region can be identified by the presence of a certain set of chrominance (i.e., C_r and C_b) values narrowly and consistently distributed in the YC_bC_r color space. RC_r and RC_b are denoted as the respective ranges of C_r and C_b values that correspond to skin color.

$$Map_{Y&C_b&C_r}(x,y) = \begin{cases} 255, & C_b \in RC_b \cap C_r \in RC_r \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where $x = 1, 2, \dots, M$ and $y = 1, 2, \dots, N$. The suitable range of the RC_r and RC_b are applied to detect the skin region.

Figure 2 illustrates the input image, extracted face region and resized face image, respectively. Next, the gray scale converting, histogram equalization and resizing processes are performed. Histogram equaliza-

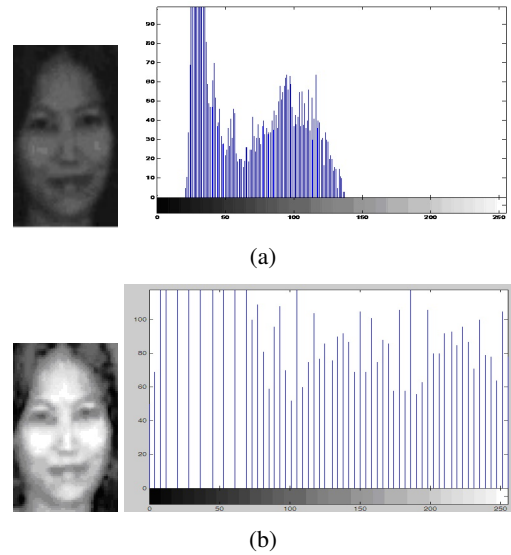


Figure 3 Histogram Equalization: (a) Gray image (b) Equalized image and histogram.

tion maps the input image's intensity values so that the histogram of the resulting image will have an approximately uniform distribution [3-6]. The histogram of a digital image with gray levels in the range $[0, L - 1]$ is a discrete function.

$$p(\gamma_k) = \frac{n_k}{n} \quad (2)$$

where L is the total number of gray levels, γ_k is the k_{th} gray level, n_k is the number of pixels in the image with that gray level, n is the total number of pixels in the image, and $k = 0, 1, 2, \dots, L - 1$. $p(\gamma_k)$ gives an estimate of the probability of the occurrence of gray level γ_k .

By histogram equalization, the local contrast of the object in the image is increased, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensity can be better distributed on the histogram. This allows the areas of lower local contrast to gain a higher contrast without affecting the global contrast. Figure 3 describes the histogram images of gray scale image and equalized image, respectively.

4. Approaches to age prediction

Human beings can easily categorize a person's age group and are often precise in this estimation. This work is based on using Eigenface to derive to a function that can predict the age of a given frontal face. Eigenface has recently gained a great deal of popularity in the computer vision community, proving to be

very successful on several classical pattern recognition problems. For the age estimation task, Eigenface is used because of its numerous appealing features. The record of the corresponding person is obtained by comparing with the estimated age group.

The idea of using Eigenfaces was partially motivated for efficiently representing pictures of faces using principal component analysis. Any collection of face images can be approximately reconstructed by storing a small collection of weights for each face and a small set of standard pictures (the Eigenpictures). The weights describing each face are found by projecting the face image onto each Eigenpicture. Face recognition, on the other hand, should not require a precise, low mean squared error reconstruction.

Each individual, therefore, would be characterized by the small set of feature or Eigen picture weights needed to describe and reconstruct him or her, an extremely compact representation when compared with the images themselves. Basing age prediction on this scheme involves an initialization phase where the Eigenfaces are constructed from face images, and a continuous processing loop where the Eigenfaces are used as a basis for prediction. The one-time initialization operations are:

1. Acquire an initial set of face images (the training set).
2. Calculate the Eigenfaces from the training set, keeping only the M Eigenfaces that correspond to the highest eigenvalues. These M images define the face space.
3. Calculate the corresponding location or distribution in M -dimensional weight space for each known individual, by projecting the face images (from the training set) onto the “face space”.

These operations can also be performed occasionally to update or recalculate the Eigenfaces as new faces are encountered. Some face images of age 21 to 25 aging group are shown in Figure 4 (a) and its mean-face are shown in Figure 4(b), respectively. Mean-face of each aging group has been computed before age prediction.

The gray converting of extracted face image and adjustment image are shown in Figure 5(a) and their differences with each Eigenface of aging group are illustrated in Figure 5(b).

Steps in age prediction

- Step 1: Convert the face image into matrix form.
- Step 2: And then find the average faces for each age group for the images in the training database.
- Step 3: Calculate the differences between the input



Figure 4 Some face images and its mean face

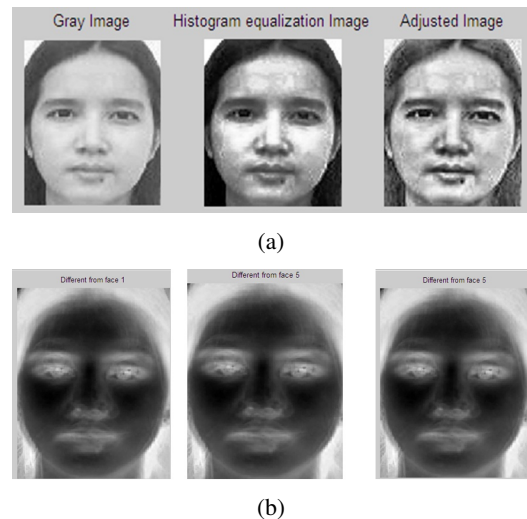


Figure 5 Extracted face image and different images

and the average faces.

Step 4: Build the Matrix A from the face differences from the average faces. Find the Covariance Matrix $Cov = AA^T$.

Step 5: Build Matrix $L = A^T A$ to reduce dimension. Find the eigenvector of Cov . Eigenvector represent the variation in faces.

Step 6: The face is projected onto the face space.

Step 7: Classify (Prediction) the face by using Euclidean distance.

In the age prediction task, the age of the subject is predicted based on the minimum Euclidean distance between the face space and each face class. Within a given database, all weight vectors of the persons within the same age group are averaged together. This creates “a face class”. When a new image comes in, its weight vector is created by projecting it onto the face space. The face is then matched to each face class that gives the minimum Euclidean distance. A ‘hit’ is occurred if the image nearly matches with its own face class. And then the age group that gives the minimum Euclidean distance will be assumed as the age of the input image.

4.0.1 Using eigenface for age prediction

Let a face image $I(x, y)$ be a two-dimensional N by N array of (8-bit) intensity values. Such an image may also be considered as a vector of dimension N^2 , so that a typical image of size 200 by 300 becomes a vector of dimension in 60,000 dimensional spaces. An ensemble of images maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principal component analysis (or Karhunen-Loeve expansion) is to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of face images called "face space". Each vector is of length N^2 , describes an N by N image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, they are referred to as "eigenfaces".

Let the training set of the faces images be $\phi_1, \phi_2, \phi_3, \dots, \phi_M$, where M is the number of images in the database. The average face of the set is defined by

$$\vec{m} = \frac{1}{M} \sum_{i=1}^M \phi_N \quad (3)$$

$$\vec{m} = \frac{1}{M} \begin{pmatrix} a_1 + a_2 + \dots + a_M \\ b_1 + b_2 + \dots + b_M \\ \vdots \\ f_1 + f_2 + \dots + f_{N^2} \end{pmatrix}$$

Where M is the number of image in database. Each face differs from the average by the vector $\tau_i = \phi_i - \vec{m}$ where τ_i is $\vec{a}_m, \vec{b}_m, \dots$ and so on.

$$\vec{a}_m = \begin{pmatrix} a_1 - m_1 \\ a_2 - m_2 \\ \vdots \\ a_{N^2} - m_{N^2} \end{pmatrix}$$

And then build the matrix A which is N^2 by M

$$A = \begin{bmatrix} \vec{a}_m & \vec{b}_m & \vec{c}_m & \vec{d}_m & \vec{e}_m & \vec{f}_m & \dots \end{bmatrix}$$

The covariance matrix which is N^2 by N^2

$$Cov = AA^T \quad (4)$$

The matrix Cov , however, is N^2 by N^2 , and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes.

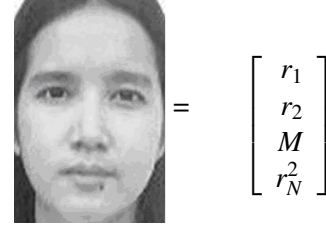


Figure 6 Face image to classify

Compute another matrix, which is M by M as, $L = A^T A$ and find the eigenvector of L . Eigenvector of Cov are linear combination of image space with the eigenvector of L .

$$U = AV \quad (5)$$

Eigenvector represents the variation in faces. Compute for each face its projection onto the face space.

$$\begin{aligned} \Omega_1 &= U^T(\vec{a}_m), \Omega_2 = U^T(\vec{b}_m) \\ \Omega_3 &= U^T(\vec{c}_m), \Omega_4 = U^T(\vec{d}_m) \\ \Omega_5 &= U^T(\vec{e}_m), \Omega_6 = U^T(\vec{f}_m) \end{aligned}$$

and so on.

To predict the age of a face image is seen in Figure 6, Prepare the matrix from the image want to predict.

And then subtract the average face for each age group from the above image matrix.

$$\vec{r}_m = \begin{pmatrix} r_1 - m_1 \\ r_2 - m_2 \\ \vdots \\ r_{N^2} - m_{N^2} \end{pmatrix}$$

A new face image (ϕ) is transformed into its eigenface components \vec{r}_m . Compute its projection on to the face space.

$$\Omega = U^T(\vec{r}_m) \quad (6)$$

The simplest method of determining face class provides the best description of an input face image or computes the distance in the face space between the face and all known faces from the following equations,

$$\xi_i^2 = \|\Omega - \Omega_i\|^2, \text{ for } i = 1, 2, \dots, M \quad (7)$$

Where Ω_i is a vector describing the i^{th} face class. The face classes Ω_i are calculated by averaging the results of the Eigen face representation over a small number of face images for each age group. The age group that gives the minimum distance will be assumed as the age of the input image.

5. Face recognition

In this paper the adaptive face recognition system is presented based on the DiaPCA and K^{th} nearest neighbor (KNN) classifier. Generally, principal component analysis methods will reduce the larger dimension of data space to the smaller intrinsic dimensionality of feature space, which is needed to describe the data economically. About the diagonal PCA and nearest neighbor classifier that will be described, the Principal Component Analysis (PCA) can do prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable. Let us consider the PCA procedure in a training set of M face images. Let a face image be represented as a two dimensional N by N array of intensity values, or a vector of dimension N^2 . Then PCA tends to find a M -dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M \ll N$) [4]. New basis vectors define a subspace of face images called face space. All images of known faces are projected onto the face space to find sets of weights that describe the contribution of each vector. By comparing a set of weights for the unknown face to sets of weights of known faces, the face can be identified. PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as:

$$S = \sum_{i=1}^M (x_i - \mu)(x_i - \mu)^T \quad (8)$$

where μ is the mean of all images in the training set and x_i is the i^{th} face image represented as a vector i . The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. A facial image can be projected onto $M' (\ll M)$ dimensions by computing

$$\Omega = [v_1 v_2 \cdots v_{M'}]^T \quad (9)$$

The vectors are also images, so called, eigenimages, or eigenfaces. They can be viewed as images and indeed look like faces. Face space forms a cluster in image space and PCA gives suitable representation. The DiaPCA is developed from PCA approach. DiaPCA can be subdivided into two components - PCA subspace training and PCA projection. During PCA

subspace training, the rows of the pixels of an $N_1 \times N_2$ image are concatenated into a one dimensional 'image vector'. In practice, only a subset of the Eigen faces ($k = 1, \dots, M'$) is retained to form a transformation matrix which is used in the PCA projection stage. Only the principal Eigen faces accounting for the most significant variations are used in the construction. A new face image vector is multiplied by the transformation matrix and projected to a point in a high dimensional DiaPCA subspace. The projected image is then saved as the face template of the corresponding user for future matching.

One of the most popular non-parametric techniques is the Nearest Neighbor Classification (NNC). NNC asymptotic or infinite sample size error is twice less than that of the Bayes error [6]. NNC gives a trade-off between the distributions of the training data with a priori probability of the classes involved [5]. K^{th} nearest neighbor classifier (KNN classifier) is easy to compute and very efficient. KNN is very compatible and obtains less memory storage. So it has good discriminative power. Also, KNN is very robust to image distortions (e.g. rotation, illumination). So this paper can produce good result by combining DiaPCA and KNN. Euclidian distance determines whether the input face is near a known face. The problem of automatic face recognition is a composite task that involves detection and location of faces in a cluttered background, normalization, recognition and verification.

6. Experimental results

Algorithms have shown good robustness and reasonable accuracy for the photos from our test set. The face database contains 11 individual groups. Within a given database, all weight vectors of the people within the same age group are averaged together. A range of an age estimation result is 15 to 60 years old, and divided into 11 classes with 5 years old range. Some face images in 11 the individual age groups are illustrated in Figure 7. The age dependent face recognition system is developed. The age prediction of the input individual is performed firstly. Then the matched individual is examined from the corresponding age group in face database based on the diagonal PCA Method. Finally, the record of the matched person is extracted.

The male individual and female individual are considered separately. The average faces for each group in the training database are also shown in Figure 8.

Figure 9 shows the Eigen faces for the age prediction system. The experimental results from the age



Figure 7 Some face images in database



Figure 8 Some Eigen faces in male database

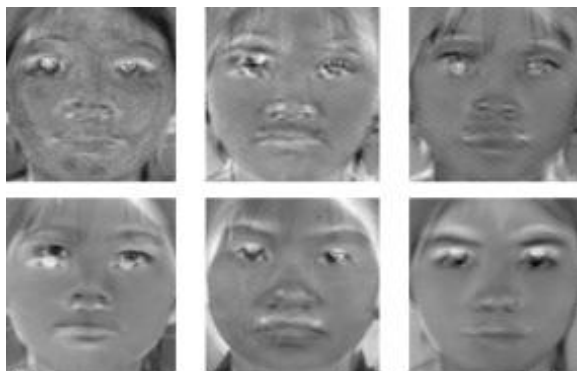


Figure 9 Some Eigen faces in female database

prediction system are shown in Figure 10.



Predicted Age: Between 15-20
Actual Age: 16 years



Predicted Age: Between 20-25
Actual Age: 23 years



Predicted Age: Between 46-50
Actual Age: 49 years



Predicted Age: Over 60
Actual Age: 79 years

Figure 10 Some experimental results for age prediction

The prediction error is occurred due to the large variation of illumination, face features and pose. The accuracy is decreased when the actual age is closed to the upper and lower boundary of aging group. The similarity errors occur at age 20 to 25 aging group and age 46 to 50 aging group. Figure 11 shows the accuracy of age prediction results for 11 aging groups.

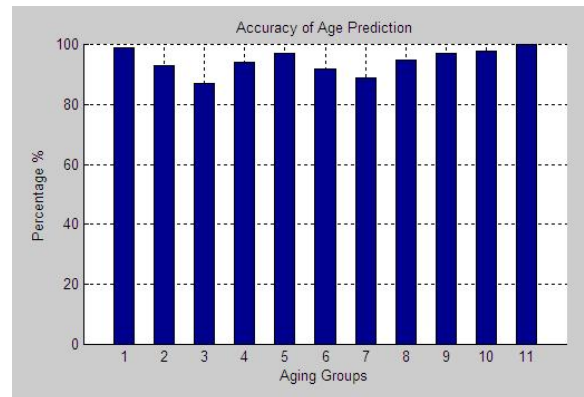


Figure 11 The accuracy graph of age prediction results

The facial recognition is performed with predicted aging group. Personal record is also extracted from the related database. Figure 12 describes the extracted record of the input individual. The recognition errors are depending on the prediction errors. Figure 13 illustrates the bar graph of recognition error of the proposed system.

7. Conclusion

The proposed technique so can be used for much real time applications like face recognition in crowded public places, banking, airport, station, highway gate, border trade, etc. Template matching technique is used for feature extraction. Figure 11 shows some experimental results in the experiments. The recognition errors about twelve percent were caused due to the large variation of the pose. The complexity and processing time will be reduced by searching the matched face from predicted age group instead of searching the face from the database which contains 11 age groups. Because of using the frontal images, we used a 2-D face model. The advantages of this paper are less processing time than only PC better features detection rate

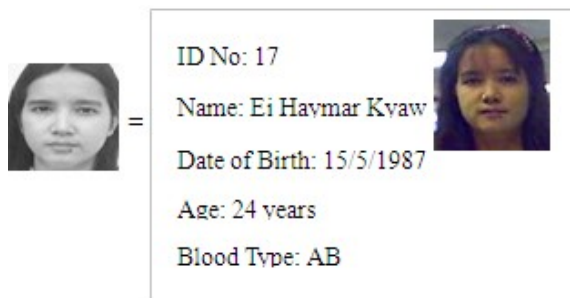


Figure 12 The extracted record for the recognized person

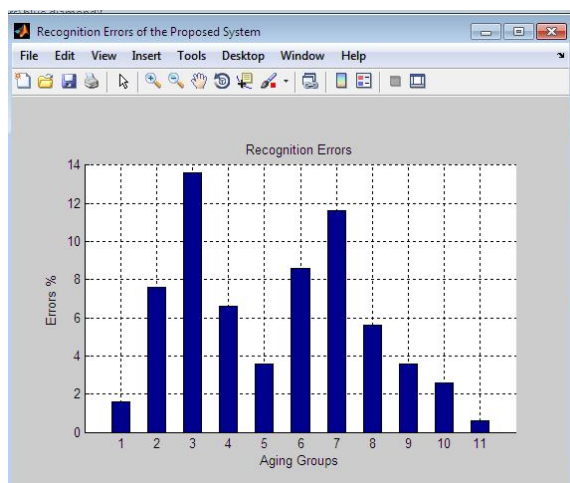


Figure 13 Recognition Errors

than conventional method that has achieved a recognition rate of 99.5% with acceptable processing time (0.36 sec). Future work includes the investigation of additional features and the application of the method to the recognition of more naturalistic facial expression videos.

Acknowledgment

Authors would like to thank Dr. Aye Min Myat, Mawbe Technological University, for allowing to use his database and Dr. Hinn Hinn Aye, University of Computer Studies, Myeik and Ms Ei Phyo Wai, University of Computer Studies, Yangon, for their valuable advice and helps.

References

- [1] A.J.O'Toole, T. Price, T.Vetter, J.C. Bartlett, and V.Blanz, "Three-dimensional shape and two-dimensional surface textures of human faces: The role of 'averages' in attractiveness and age", *Image and Vision Computing Journal*, Vol.18, No.1, pp.9-19, 1999.
- [2] Khoa Luu, tien Dai Bui, Ching Y.Suen and Karl Ricanek Jr., "Spectral Regression based Age Determination", *IEEE 2010*.
- [3] Kwon, Y.H. and da Vitoria Lobo, N.1993. "Locating Facial Features for Age Classification". In *Proceedings of SPIE-the International Society for Optical Engineering Conference*. 62-72.
- [4] Hayashi, J., Yasumoto, M., Ito, H., Niwa, Y. and Koshimizu, H.2002. "Age and Gender Estimation from Facial Image Processing". In *Proceedings of the 41 st SICE Annual Conference*. 13-18.
- [5] Lanitis, A. 2002. "On the Significance of Different Facial Parts for Automatic Age Estimation". In *Proceedings of the 14 the International Conference on Digital Signal Processing*. 1027-1030.
- [6] J.R. Sclar, P. Navarreto, "Eigen space-based FACE recognition: a comparative study of different approaches IEEE Tran", *System man and Cybernetics-part C: applications*, Vol-35, No.3, 2005.
- [7] J. Yang, D. Zhang, A. F. Frangi, J. Y. Yang, "Two-dimensional PCA: a new approach to

appearance-based face representation and recognition”, *IEEE Trans on Pattern Analysis and Machine Intelligences* 26(1)(2004) 131-137.

- [8] Hlaing Htake Khaung Tin and Myint Myint Sein, “Race Identification for face Images”, *International Journal on Information Technology* (IJIT 2011), August 2011.
- [9] Hlaing Htake Khaung Tin, “Facial Extraction and Lip Tracking Using Facial Points”, *International Journal of Computer Science, Engineering and Information Technology* (IJCEIT 2011), Vol.1, No. 1, April, 2011.