University of Sindh Journal of Information and Communication Technology
(USJICT)
Volume 4, Issue 2, July 2020

ISSN-E: 2523-1235, ISSN-P: 2521-5582
Website: http://sujo.usindh.edu.pk/index.php/USJICT/

Ear Biometric for Human Authentication

Abid Ullah, Said Khalid Shah, Muhammad Ayaz

University of Science and Technology, Bannu, Pakistan
adwazir1@gmail.com, skhalids2000@yahoo.com

Abstract: This paper describes Ear identification system and using Ear as a biometric organ for human authentication. It uses Principal Component Analysis (PCA) algorithm to identify ear features. The proposed system consists of six basic steps. In first step, 2D Ear image is capture by camera. The second step is to crop ear image as a region of interest and normalized in the third step. In the fourth step PCA algorithm is applied to the image to generate eigenvalues and eigenvectors. In the fifth step, ear along with eigenvalues and eigenvectors are generated as an output of PCA. Finally (last step) the image is compare with stored images in the database. We tested the system using images obtained from different international databases as well as our own created database. Our system accuracy is nearly 99.5%.

Keywords: Ear Biometric; Human Authentication; PCA

I. INTRODUCTION

Data is an asset for an organization. The protection of such data from unauthorized users requires a comprehensive mechanism to avoid privacy leakage. There are different security systems. The most common security system is password that fails in some cases especially when we use it for human authentication [1]. For this purpose we use biometric system. There are two types of biometric system, one is physical and the other is behavioral biometric. The physical biometrics are related with physical characteristics of the person such as fingerprint, iris, face recognition, hand geometry etc where behavioral biometric is related with behavioral characteristics of the person, such as voice, signature and gait [2], [3]. All these biometric characteristics have some problems, for examples face recognition has expression and makeup problems. In fingerprint the line of the finger may damage with the passage of time, where in iris we used different fashion lens which create problem in iris recognition. To overcome all these problems, Ear is one of the most suitable organ, because it neither change with expression nor damage with the passage of time. Unlike fingerprint, iris and face, it can be captured from a distance without the cooperation of the subject. According to medical point of view Ear size increases proportionally after the four months of birth up to age of eight and after that it remains constant until to the age of seventy [1].

Human Ear using as a biometric organ have the following four basic properties.

1) Universality: Every person must have the universality characteristic.
2) Distinctiveness: Different people have different characteristics.
3) Permanence: The characteristic of the people should be invariant with the passage of time.
4) Collectability: The characteristics of a human can be measured quantitatively.

II. BACKGROUND STUDY OF THE EAR

In 1906, for the first time Imhofer found four properties of the Ear which are unique in the set of 500 Ears [4]. In 1989 Iannarelli experimented on 10000 Ears of different peoples and examined that no identical Ear was found [5]. Iannarelli developed a technique for Ear identification which is called anthropometric. In this technique Iannarelli used 12 different measurement techniques. Moreno et al worked on 2D. He used neural net approaches to recognize the ear image [6]. He tested a gallery of 48 persons and obtained 93% recognition rate. Victor and Chang used PCA for combination of face and Ear but Ear result was not better than face [7], [8]. Yuizone used genetic search for the recognition of 2D Ear image [9]. Bhanu and chen used 3D Ear recognition system [10]. They used local surface shape technique. They achieved 100% recognition rate. Hurley et al used force field transformation to extract novel features [11]. In this technique the vector was used to represent the image which was invariant to scale, noise, initialization and rotation. The experiment extracts the 2D Ear. He used 252 images from 63 subjects 4 images per subject. He got 99.2% result. Moon and Pun surveyed on the literature of the Ear biometric [12]. In 2018 Alagarsamy, S.B and Kondappan used Runge–Kutta (AARK) threshold segmentation with ANFIS classification technique, in this technique they used threshold segmentation to find the threshold value of the region to be segmented [13]. A. A. Almisreb, N. Jamil and N. M. Din used AlexNet Convolution Neural Network (AlexNet CNN) for ear recognition. They used 250 images of ear taken from 10 subjects for training purpose and 50 images are used for testing. They get 100% validation accuracy[14]. Ali, Abdelmgeid, Alshazly Hammam and M. Hassaballah used local binary patterns (LBP) features technique to recognition ear image. They used average local binary patterns (ALBP) they used publicly dataset namely AWE, WPUT, AMI, IIT Delhi-I AND IIT Delhi-II. The recognition was 99% [15]. Finally; a conclusion is presented to summarize the main outcomes of this research.

III. Proposed Systeim

The proposed system is developed in MATLAB. The system architecture is given in Figure 1.

1) In the first step side face image (raw image) is captured by camera which is connected to the PC.
2) In step 2 the raw image is preprocessed in which the Ear image is cropped as a region of interest (ROI) as shown in Figures 2.
3) In the third step Ear image is normalized. In normalization, the image is converted to grayscale and resized up to 200 × 150 dimensions as shown in Figures 2.
4) In step four we applied Principal Component Analysis (PCA) on image, which generates eigenvectors and eigenvalues and we chose the eigenvectors which have the highest eigenvalues.
5) The Ear (JPEG image) along with eigenvectors and eigenvalues is the output of PCA.
6) In this step, the resultant image with eigenvectors is checked in the training database if image is present in the database then it shows the image along with a message of recognition or error message.

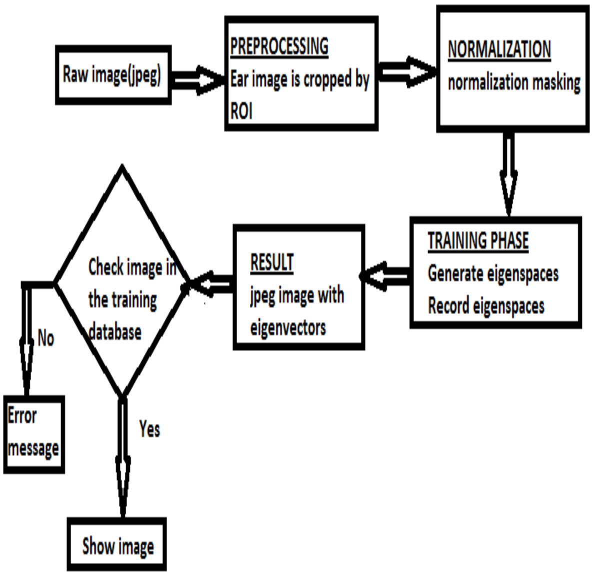

Figure 1. System Architecture

a) Left image b) Right image

Figure 2. Before cropping and normalization, b) Right image after being cropped and normalized.

IV. Eigenvectors and Eigenvalues of the Image By Principal Component Analysis

To find eigenvectors and eigenvalues the following Steps are used.

The Eigenvectors of a linear operator in linear algebra are non-zero. When the linear operator is applied on those Eigenvectors they result in to a scalar multiple of them. (λ) is called the Eigenvalue associated with the Eigenvectors (Y). The eigenvector is the property of a matrix. When the operation on a matrix is performed then only the magnitude of Eigenvector is changed and its direction remains the same

$$BY = \lambda Y \quad (1)$$

Where B is a vector function

$$(B - \lambda I)Y = 0 \quad (2)$$

When there is non-trivial solution exists then

$$Det(B - \lambda I) = 0 \quad (3)$$

"Det" is the determent and B has 'N' Eigenvalues which satisfies the equation.

$$BY_i = Y_i \lambda_i \quad (4)$$

Where i = 1, 2, 3………n

A. Representation of Image

Ears images are represented by Ʈ$_1$, Ʈ$_2$ Ʈ$_3$… Ʈ$_M$. The features vectors are stored in 2D and converted into one dimension, Ʈ1 is one dimension.

For Example $\begin{bmatrix} 1 & 2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix}$

Where vector Ʈ$_i$ represents each image.

$$Ţ_1 = \begin{bmatrix}1\\2\\1\\3\end{bmatrix} Ţ_2 = \begin{bmatrix}1\\5\\1\\-3\end{bmatrix} \ldots\ldots\ldots\ldots Ţ_M = \begin{bmatrix}1\\2\\-2\\1\end{bmatrix}$$

B. Mean and Mean Centered Images

Mean center images calculated as

$$\psi = (1/M) \sum_{i=0}^{M} Ţ_i \tag{5}$$

$$\begin{bmatrix}1\\2\\1\\3\end{bmatrix} + \begin{bmatrix}1\\5\\1\\-3\end{bmatrix} +\ldots\ldots\ldots\ldots.+ \begin{bmatrix}1\\2\\-2\\1\end{bmatrix} = \begin{bmatrix}a\\b\\c\\d\end{bmatrix}$$

$$\psi = (Ţ1 + Ţ2 + Ţ3 + \ldots\ldots\ldots..ŢM)/M \tag{6}$$

The difference between each Ear and average can be calculated as

$$\Phi i = Ţ_i - \psi \tag{7}$$

$$\Phi_1 = \begin{bmatrix}0\\-1\\-1\\-3\end{bmatrix} \Phi_2 = \begin{bmatrix}5\\2\\4\\-3\end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots \Phi_M = \begin{bmatrix}4\\3\\0\\2\end{bmatrix}$$

C. Covariance Matrix

A covariance matrix can be defined as

$$X=BB^T \tag{8}$$

Where $$B=[\Phi_1, \Phi_2 \ldots \Phi_M] \tag{9}$$

Suppose the eigenvectors Vi of $B^T B$ is

$$B^T BY_i = \lambda_i Y_i \tag{10}$$

Eigenvectors of B^T B are Y_1, Y_2 which are in 2×1 form. Multiplying the above equation by B.

$$BB^T BY_i = B\lambda_i Y_i \tag{11}$$

$$BB^T(BY_i) = \lambda_i(BY_i) \tag{12}$$

Each Eigenvector related to BB^T can be calculated easily by reducing the dimensions, where λi is the Eigenvalue and BY_i is the Eigenvector.

D. Eigen Ear Space

In the Ear space, the Ear image can be projected as

$$\Omega_k = Z^T (Ţ_K - \psi) \tag{13}$$

Z^T shows the image of Ear which look ghostly and it is called the Eigen Ear. K= 1,……M, where ($Ţ_K$ - ψ) is the mean centered image. So image1 can be projected by Ω1, image2 by Ω2 and so on

E. Recognition Step

In the Ear space, the test image Ţ is projected in order to obtain a vector Ω where Ω is represented as

$$\Omega = U^T(Ţ - \psi) \tag{14}$$

Where Ω is the distance to each Ear which is called Euclidean distance and represented by

$$€_K^2 = [\Omega - \Omega]2 \tag{15}$$

K=1… M where Ω_K is a vector describing the k^{th} Ear class. The class K has some Ear with minimum €K below to choose some threshold Θ_C otherwise, the Ear recognition is unknown. Between any two Ears images, Θ_C is the half largest distance.

$$\Theta_C = (1/2) \max j;k \left[\left[\Omega_j - \Omega_k\right]\right] \tag{16}$$

k = 1… M. We have to find the distance € between the original test image Ţ and its reconstructed image from the Eigen Ear $Ţ_f$. [13]

$$€_2 = [[Ţ - Ţ^f]].^2 \tag{17}$$

Where $$Ţ^f = U^* \Omega + \psi \tag{18}$$

If € ≥ Θ_C then input image is not even an Ear image and not recognized.
If € < Θ_C and € ≥ Θ_C for all K then input image is an Ear image but it is recognized as unknown Ear.
If € < Θ_C and $€_K < \Theta_C$ for all K then input images are the individual Ear image associated with the class vector Ω_K [16].

V. EXPERIMENTAL DATA

We have collected images from different international databases such as "Ear database" [17], "IIT Delhi Ear Database" [18] and from "University of science and technology Beijing" (USTB) [19]. "Ear database" collected from http://matlab-recognition-code.com/ear-recognition-system(system V3). It consists of total 175 images from 25 subjects 7 images per subject with different angles of both ears (Right and left). Each ear has a dimension of 492 × 702. From "IIT Delhi Ear Database" we collected samples of the ears images and also from "USTB". IIT Delhi samples ears images database consists of 12 images from 4 different subjects. All the subjects in the database are in the age of 14-58 years. The resolution of these images is 272×204. The USTB samples ears images databases consist of three different phases of image database I, image database II and image database III; image database II has different light illuminations and angle variations. The distance between the camera and subject is fixed to 2 meters. Total four images are taken from each subject. Two images are taken under different lighting condition while two images are taken with different angles. One with +30 and other is with -30 degree. Each image has a resolution of 300 × 400. Image database III consists of images with different angles from 0 degrees to 60 degree where the camera is perpendicular to ear at 0 degrees. The angle increased from 5 degrees up to 60 degree and on each 5 degrees 2 images were taken and the distance from the camera is 1.5 meters. The resolution of the image is 768 × 576. One image was taken from the front of the ear other was taken +45 degree and third was taken -45 degree from the front image. Each image has a resolution of 3096 X 4128. The distance between the camera and ear is taken 2 feet, images consists of both hair and no hair subject for which we got 100% recognition rate.

A. Our Own Created Database

We have created our own dataset which consist of 33 images of 11 different subjects, 3 images per subject. One image is taken from the front of the ear other was taken +45 degree and third was taken -45 degree from the front image. Each image has a resolution of 3096 × 4128. The distance between the camera and ear is 2 feet. Images consist of hairy and non- hairy.

VI. EXPERIMENTAL RESULT AND ANALYSIS

For experiment, we have created two database folders, testing database and training database. Testing database consist of those images which we use for testing while training database consist of those images which are recognizable. There are seven different poses of images in the testing database and the same images are placed in training database. We took 1st image (Front_image) from the testing database (see figure 3) and against this image there are seven images with different poses in the training database (see Figures 4). When applied the PCA it recognized the "Front_image" which have the same pose (see Figure 5). When moving "Front_image" to the last position in the testing database then it recognized "zoom_image" (other pose) in the training database (see Figure 6). This experiment is repeated for all databases.

The results have been analyzed as False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). Table 1 shown FAR, FRR and EER values for different databases.

Figure 3. Front_image in the testing database

Figure 4. 7 Images with different poses in the Training Database

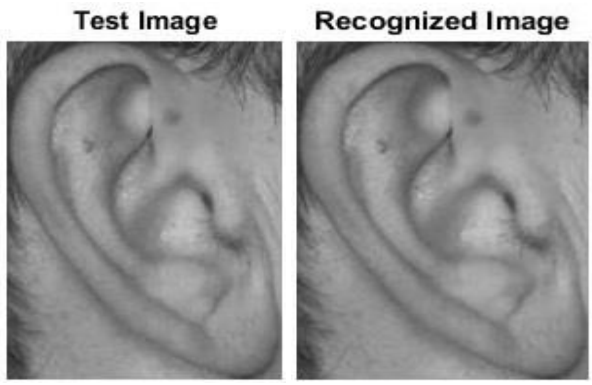

Figure 5: Recognized image (Front_image) which has the same pose

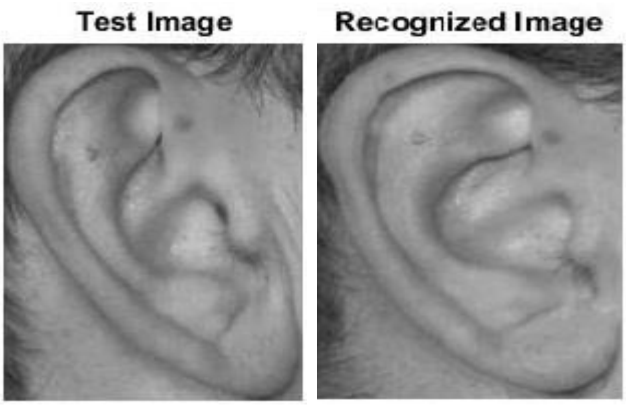

Figure 6: Recognized image (zoom_image) which has different pose

TABLE I. FAR, FRR AND EER VALUES FOR DIFFERENT DATASETS

DATASETS	FAR	FAR%	FRR	FRR%	EER
SYSTEM V3	0.05	5	0	0	2.5
SAMPLE OF IIT DELHI EAR DATABASE	0.05	5	0	0	2.5
SAMPLE OF USTB	0	0	0	0	0
OUR OWN CREATED DATABASE	0	0	0	0	0

We compared different techniques and there results in table 2

TABLE II. COMPARISON WITH OTHER TECHNIQUES AND THERE RESULTS IN TABLE 2.

	3D/2D	MODALITY	PERFORMANCE	DATASET
MORENO	2D	NEURAL NET	93%	168
MU	2D	GEOMETRIC	85%	308
HURLEY	2D	FORCE FIELD	99.2%	252
CHAN		ICP	90.4%	104
YAN	3D	ICP	97.8%	1386
OUR WORK	2D	PCA	99.5%	250

VII. CONCLUSION

We used Principal Components Analysis (PCA) for image recognition which is the base for all Algorithms. PCA is one of the best algorithms for 2D recognition. We have experiment on different international databases and our own created database which gives nearly 99.5% recognition rate for all databases (IIT Delhi, USTB, system V3 and our own created database). Ear is cropped from the side face image from the region of interest which minimize the angle limitation up to some extent. In future to increase the recognition rate use different algorithm. One way to increase the recognition rate is to detect Ear edge and eliminate all non-Ear area Light condition can also affect the recognition rate if light is low then it will decrease the recognition rate. If we control this problem then it will increase the recognition rate.

References

[1] F. Khursheed, and A. H. Mir, “Image Processing and Pattern Recognition” International Journal of Signal Processing, Vol.7, No.3 pp.347-360 (2014).

[2]A. K. Jain, P. Flynn, and A. A. Ross, Hand book of biometrics. New York: Springer, 2007

[3]D. Maltoni et al., Hand-book of Fingerprint Recognition. Springer-Verlag New York, Inc., New York, NY, 2003. E-bok tilgjengelig for eierbibliotek via Internet.

[4] A.J. Hoogstrate, H. Van Den Heuvel, and E. Huyben., “Ear identification based on surveillance camera images”, Sci Justice, 41: 167-172, 2001.

[5] A. Iannarelli., “Ear Identification”. Paramont Publishing Company, 1989.

[6] B. Moreno, A. Sanchez, and J. Velez, “On the use of outer ear images for personal identification in security applications”, In Pro. IEEE 33rd Annual Intl. Conf. on Security Technology, pages 469-476 1999.

[7] K. Chang, K. Bowyer, and V. Barnabas, “Comparison and combination of ear and face images in appearance-based biometrics”, IEEE Transaction on Pattern Analysis and Machine Intelligence, 25:1160–1165, 2003.

[8] B. Victor, K. Bowyer, and S. Sarkar, “An evaluation of face and ear biometrics”, In 16th International Conference of Pattern Recognition, pages 429–432, 2002.

[9] T. Yuizono, Y. Wang, K. Satoh, and S. Nakayama, “Study on individual recognition for ear images by using genetic local search” In Proceedings of the 2002 Congress on Evolutionary Computation, pages 237–242, 2002.

[10] B. Bhanu and H. Chen., “Human ear recognition in 3D” In Workshop on Multimodal User Authentication, pages 91–98, 2003.

[11] D. Hurley, M. Nixon, and J. Carter., “Force field energy functional for image feature extraction” Image and Vision Computing Journal, 20:429–432, 2002.

[12] K. Pun and Y. Moon., “Recent advances in ear biometrics” In Proceedings of the Sixth International Conference on Automatic Face and Gesture Recognition, pages 164–169, May, 2004.

[13] Alagarsamy, S.B., Kondappan, S. “Ear recognition system using adaptive approach Runge–Kutta (AARK) threshold segmentation with ANFIS classification”. Neural Comput & Applic 32, 10995–11006 (2020)

[14] A. A. Almisreb, N. Jamil and N. M. Din, "Utilizing AlexNet Deep Transfer Learning for Ear Recognition," 2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP), Kota Kinabalu, 2018, pp. 1-5

[15] Hassaballah, M. & Alshazly, Hammam & Ali, Abdelmgeid. (Ear recognition using local binary patterns: A comparative experimental study. Expert Systems with Applications. 118. 182-200 (2019).

[16] M. A. Turk and A. P. Pentland., “Face recognition using eigenfaces” In IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 91, pages 586 -591, 1991

[17] https://www.matlab-recognition-code.com/ear-recognition system-matlab-full-source-code.

[18] https://www4.comp.polyu.edu.hk/~csajaykr/IITD /Database_Ear.htm

[19] http://www1.ustb.edu.cn/resb/en/visit/visit.htm