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Ear Biometrics- An Alternative Biometric

R. Parimala[1] and C. Jayakumar[2]
[1]*Research Scholar, Bharathiar University, Coimbatore, India*
[2]*Professor, CSE Department, RMK Engineering College, Kavaraipettai ,India*
[1]*parimalasuresh80@gmail.com,* [2]*cjayakumar2007@gmail.com*

Abstract:
This paper is one of the parts of a biometric based identity verification security system development project. Today, the most successful biometric based identification technologies such as fingerprint and iris scan are used worldwide in both criminal investigations and high security facilities. Even though Face recognition is one of the developing biometric methods; illumination, makeup, posing, emotional expressions and face-lifting reduce the success of face recognition. A new biometric which is not effected by any of the factors above is needed. The alternative biometric should overcome the drawbacks of face recognition. Twins are identical but their ears differ from each other, ear is also 3-dimensional but it is simpler than face and emotional expressions do not affect the ear. In the light of this, ear is a good alternative to face, as a biometric. In this study, the methods presented in the literature are tested on ear images. These methods are linear classification algorithms that work on 2D image databases. It is found out that, PCA, FLD, modified FLD which is also known as DCVA and LPP has better results at ear recognition than face recognition. Ear recognition has higher hit rates, when compared with face recognition researches that are presented in the literature previously. The results of this study proved that ear is the best alternative to face at personal identification tasks.

Introduction

Ear recognition is considered to be a part of pattern recognition technology. Ear recognition and recognition of moving people in natural scenes require a set of visual activities to be performed. This process consists of three tasks: detection, normalization and recognition. Detection means the detection and tracking of ear-like image patches in dynamic scenes. Normalization is the segmentation, alignment and normalization of the ear images and finally recognition is the presentation and modelling of ear images as identities, and the association of novel ear images with known models [1]. A number of approaches for recognition and classification tasks have been proposed in the literature. These can be classified as Principal Components Analysis (PCA) [2,3,4], Fisher's Linear Discriminant (FLD) [2,5,6], Discriminative Common Vectors (DCV) [4] and Locality Preserving Projections (LPP) [5,6,10]. Techniques like PCA and FLD treat the ear image as a vector in a high-dimensional space and derive a lower dimensional representation (in the case of PCA) or a discriminatory representation (in the case of FLD). FLD provides a better performance but it is computationally more intensive compared to feature-based approaches. Also, the performance of data analysis techniques depends on the training data. Discriminative Common Vector approach (DCVA) reduces computational cost in recognition stage because a common vector is chosen from each class, instead of dealing with all ears in the dataset. LPP tries to preserve local structure of ear images for classification, however, PCA, FLD and DCVA focus on global structure of ear images [5,6]. Comparison of ear and face, using one or two recognition methods is the topic of previous research papers [7,8]. This study will compare the performance of four most well-known traditional and new recognition algorithms at ear recognition task, for the first time. In this work we extend existing surveys on ear biometrics, such as [11,12,13,14,15,16]. Abaza et al. contributed an excellent survey on ear recognition in March 2010. Their work covers the history of ear biometrics, a selection of available databases and a review of 2D and 3D ear recognition systems.

1.1 Applications of Ear Recognition

The applications of Ear Recognition Techniques (ERT) can be divided into commercial and law enforcement applications. ATMs, safe deposit boxes and ear recognition based security systems can be thought of commercial applications of ear recognition. There are surveillance cameras at all banks and ATMs. These cameras can be repositioned to record both the faces and ears of customers. In the case of robbery both ear and face images of suspects can be analyzed to identify them. These kinds of precautions make the security policies of banks stronger. Another example is an ear recognition system can be placed at the entrance of a parking lot and the gate opens if the driver is a known person. These kinds of applications can also be used at high-tech facilities where security is mandatory. These are all commercial examples. If law enforcement applications are considered, there are many wanted people all over the world. If the records of surveillance cameras, which are placed at crowed places like squares, train stations and airports, are processed by the algorithms such as ear and face recognition simultaneously, detecting and arresting these wanted people become easier [9,10]. So world becomes a safer place.

1.2 Stages in Ear Recognition

The definition of ear recognition task is to identify one or more people in a scene using a stored database of ears. The solution of the general problem is divided into three different stages:

- Segmentation of ears from cluttered scenes.
- Extraction of features from the ear region.
- Decision.

Segmentation is usually achieved by the following algorithm. An edge map is created, and then edges are connected together using several heuristics and the edges are matched into an elliptical shape using a Hough transformation. If the input is composed of video images (moving objects), motion could be used for segmentation. The second and most important stage is the extraction of features. There are two types of features: holistic features and partial features. Partial features techniques use crucial points in the ear for recognition, whereas holistic feature techniques always consider the ear as a whole. For example PCA is a holistic feature technique. In the last stage, using the data collected in the previous stages a decision is made.

There can be three types of decisions that can be made depending on the application:
1.Identification: where labels for each individual must be obtained;
2.Recognition of a person: where a decision is made based on the ear that the individual has already been seen, and;
3.Categorization; in which the ear must be assigned to a certain category [1]. This study will focus on two stages of ear recognition: extraction of features and decision.

2. Ear Recognition Algorithms

2.1 Principal Component Analysis (PCA)

There are patterns that occur in any input signal (image). Such patterns, which can be observed in all signals, could be - in the domain of ear recognition - the presence of some objects, such as helix, antihelix and ear lobe, in any ear as well as relative distances between these objects. These characteristic features are called eigenears (principal components) in ear recognition domain. They can be extracted out of the original image data by means of a mathematical tool called Principal Component Analysis (PCA). By means of PCA each original image of the training set can be transformed into a corresponding eigenear. Furthermore, an important feature of PCA makes possible to recontruct any original image from the training set by combining the eigenears. Eigenears are the characteristic features of the ear, the original ear image can be reconstructed from eigenears if all the eigenears (features) are added up in the right proportions. Each eigenear represents certain features of the ear, which may or may not be present in the original image. If the feature is present in the original image to a higher degree, then the share or sum of the corresponding eigenear should be greater. If the particular feature is not (or almost not) present in the original image, then the corresponding eigenear should contribute a smaller (or not at all) part to the sum of eigenears. so, in order to reconstruct the original image from the eigenears, one has to build a kind of weighted sum of all eigenears. That is, the reconstructed original image is equal to a sum of all eigenears, with each eigenface having a certain weight. This weight specifies, to what degree the specific feature (eigenear) is present in the original image. Eigenears that are extracted from original images can exactly reconstruct back these images. It is also possible to reconstruct original images approximately by using some of eigenears. Losses due to omitting some of the eigenears can be minimized by choosing the most important features (eigenears). The omission of eigenears is necessary due to scarcity of computational resources. It is possible to extract the ear from eigenears that is given by a set of weights. It is also possible to extract the weights from the eigenears and recognize the ear. These weights tell the amount by which the ear in question differs from typical ears represented by the eigenears.

Weights can determine two important things;
1. Determine if the image in question is a ear at all. If the weights of the image differ a large degree from the weights of ear images (ie. images that are ears for sure), the image probably is not a ear.
2. Similar ears (images) possess similar features (eigenears) to similar degrees (weights). If one extracts weights from all the images available, the images could be grouped into clusters. That is, all images having similar weights are likely to be similar ears. Consider ear as a 2D image. This image can be formed as a vector. Suppose that width of the image is w pixels and height of the image is h pixels. Thus the number of pixels for each vector is w*h. to construct the vector, the rows of the image are put beside each other as shown in Figure 2.1 and Figure 2.2

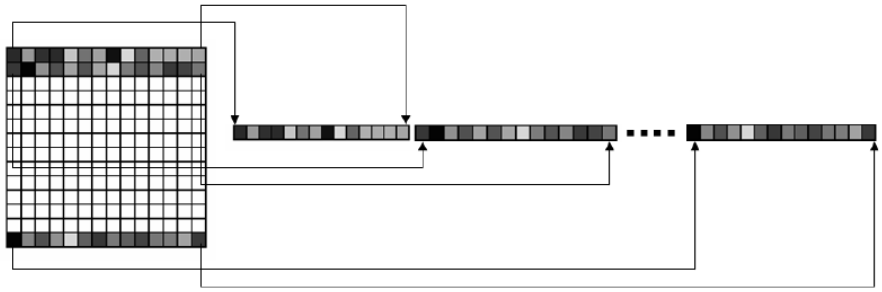

Figure 2.1: Construction of ear vector [1]

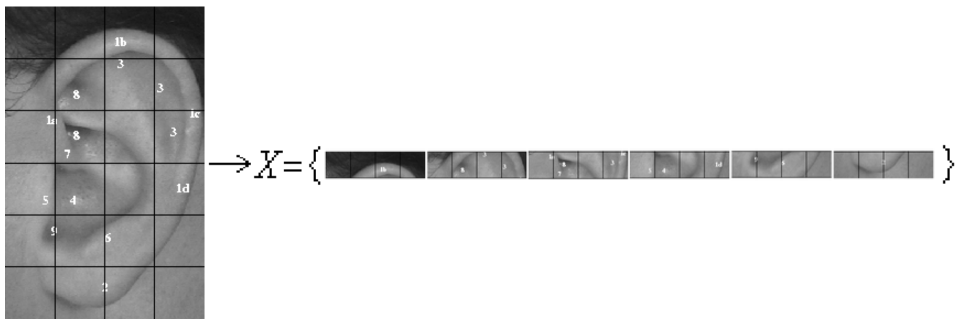

Figure 2.2: Formation of the vector of ear from the image of ear. 1 Helix, 2 Lobule, 3 Antihelix, 4 Concha, 5 Tragus, 6 Antitragus, 7 Crus of Helix, 8 Triangular Fossa, 9 Incisure Intertragica

The ear vector belongs to an ear space. This space is the image space, the space of all images whose dimensions are w by h pixels. All the ears look like each other. They all have helix, antihelix, ear lobe, etc. located at the same place. There for, all the ear vectors are located in a very narrow cluster in the image space. The full image space is not an optimal space for ear description. The task presented here aims to build an ideal ear space that describes the ear better. The basis vectors of this ear space are so called eigenears (principal components) [3]. In the field of recognition one of the most-preferred, because of its simplicity and accuracy, methods is Principal Components Analysis. PCA is based on the Karhunen-Loeve (K-L) or Hotelling Transform, which is the optimal linear method for reducing redundancy, in the least mean squared reconstruction error sense. The idea of PCA is based on the identification of linear transformation of the co-ordinates in a system: The three axis of the new coordinate system coincide with the directions of the three largest spreads of the point distributions. PCA uses the singular value decomposition to compute the principal components. A matrix whose rows consist of the eigenvectors of the input covariance matrix multiplies the input vector. This produces transformed input vectors whose components are ordered according to the magnitude of their variance. Those components, which contribute only a small amount to the total variance in the data set, are eliminated. It is assumed that the input data set has already been normalized so that it has a zero mean. The most important components of each ear are located in a very narrow cluster. Thus the full image is not an optimal space for ear recognition and there are many redundant components that are not important for ear recognition. The purpose of PCA is to reduce the dimension of the set or the space. That means it aims to catch the total variation in the set of the training ears, and to explain this variation by few variables. Dealing with few variables is always more advantageous than dealing with huge numbers of variables, especially if there are huge number of ears to be processed.

2.2 Fisher's Linear Discriminant (FLD)

The main idea of PCA is to find components that are useful for representing data, but it is not guaranteed that these components are useful for discriminating between data in different classes. In some cases, the directions that are discarded by PCA might be exactly the directions that are needed for distinguishing between classes. For example, if the data is uppercase letters O and Q, PCA might discover the gross features that characterize Os and Qs, but might ignore the tail that distinguishes an O from a Q. Where PCA seeks directions that are efficient for representation, discriminant analysis seeks directions that are efficient for discrimination [2].

The implementation of FLD was done on a 2D random dataset. The purpose of this process is to show how FLD works. Different from PCA, FLD handles dataset as divided into classes and tries to find the best direction for the good classification. The dataset is divided into 2 classes as shown in Table 2.1 .

Table 2.1: Dataset Divided into 2 Classes

		X	Y
CLASS 1	P2	1	2
	P4	2	3
	P7	3	3
	P8	4	5
	P10	5	5

		X	Y
CLASS 2	P1	1	0
	P3	2	1
	P5	3	1
	P6	3	2
	P9	5	3
	P11	6	5

Mean of class μ_1 and μ_2 were calculated by the formula given in Eq. (2.1) and shown below;

$$\mu_1 = mean(c_1) = [3\ 3.6]$$

$$\mu_2 = mean(c_2) = [3.3\ 2]$$

Scatter matrices S_1 and S_2 for each class were calculated by the formula given in Eq. (2.2) and shown below;

$$S_1 = \begin{bmatrix} 10 & 8 \\ 8 & 7.2 \end{bmatrix}$$

$$S_2 = \begin{bmatrix} 17.3 & 16 \\ 16 & 16 \end{bmatrix}$$

Within the class scatter matrix *W S* of dataset was calculated by the formula given in Eq. (2.3) and shown below;

$$S_w = S_1 + S_2 = \begin{bmatrix} 27.3 & 24 \\ 24 & 23.2 \end{bmatrix}$$

Between the class scatter matrix *B S* of dataset was calculated by the formula given in Eq. (2.4) and shown below;

$$S_B = \begin{bmatrix} 0.09 & -0.48 \\ -0.48 & 2.56 \end{bmatrix}$$

After calculating the within the class scatter matrix *W S* and between the class scatter matrix *B S* , the generalized eigenvalue problem, given in Eq. (2.5), was solved and $c - 1$ most significant eigenvector, which has the larger eigenvalues, was taken to form projection direction. In this case there are two classes so there is just one eigenvector, which is shown below;

$$w = \begin{bmatrix} -0.67 \\ 0.75 \end{bmatrix}$$

2.2.2 Multiple Discriminant Analysis

For the c-class problem, the natural generalization of Fisher's linear discriminant involves c -1 discriminant functions. Thus, the projection is from a d-dimensional space to a (c -1)-dimensional space, and it is tacitly assumed that $d \geq c$. The generalization for the within-class scatter matrix is obvious:

$$S_W = \sum_{i=1}^{c} S_i \qquad (2.6)$$

If we check the two-class case, we find that the resulting between-class scatter matrix is $n1n2 / n$ times our previous definition. The projection from a d-dimensional space to a ($c - 1$)-dimensional space is accomplished by $c - 1$ discriminant functions

2.3 Small Sample Size Problem

In ear recognition tasks, the dimension of the sample space is typically larger than the number of the samples in the training set. So the within-class scatter matrix is singular. This problem is known as the small sample size problem [1,2]. To overcome this problem, a new method is proposed called Discriminative Common Vector method, which is based on a variation of Fisher's Linear Discriminant Analysis for small sample size. This algorithm uses within-class scatter matrix to produce common vectors. Then the common vectors are used for classification of new ears. This method claims more accuracy, efficiency and stability comparing to traditional methods like PCA and FLD.

2.3.1 Problems with PCA

PCA is unsupervised since it does not consider the classes within the training set data. In choosing a criterion that maximizes the total scatter, this approach tends to model unwanted within-class variations such as those resulting from the differences in illumination and other factors. Also, because the criterion does not minimize the within-class variation, there could be overlap in the result compared to other methods. Thus, the projection vectors chosen for optimal reconstruction may obscure the existence of the separate classes.

2.3.2 Problems with FLD

FLD solves the limitations of the Eigenears method by applying Fisher's Linear Discriminant criterion as mentioned below;

$$\boldsymbol{J_{FLD}(W_{opt}) = arg_w max\, |W^T S_B W| / |W^T S_w W|} \qquad \textbf{(3.69)}$$

where *B S* is the between-class scatter-matrix and *W S* is the within-class scatter matrix. By applying this method, the projection directions maximize the Euclidian distance between the ear images of different classes on the other hand and on the other minimize the distance between the ear images of the same class. The problem in this method is that it cannot be applied since the dimension of the sample space is typically large than the number of samples in the training set. Discriminative Common Vector approach is one of the algorithms those were proposed to fix this problem [4].

2.4 **Discriminative Common Vector Approach (DCVA)**

Since ear images have similar structure, the image vectors are correlated, and any image in the image space can be represented in a lower-dimensional subspace without losing a significant amount of information. The Eigenear method has been proposed for finding such a lower-dimensional subspace. In DCVA, the Vector spaces are arrived using LPP mathematical formulation.

3.Results and Discussions

PCA

Ear Location	Dimension Number (Number of Feature Vectors)	Hit Rate (Random Sampling)	Hit Rate(K-Fold Cross validation)
Left	4	58.6	58.6
	8	82.4	89.1
	16	91.6	89.4
	32	95.9	93.6
	64	96.8	93.5
	128	97.1	94.8
Right	4	64.8	61.4
	8	87.7	84.6
	16	95.6	92.9
	32	98.9	96.8
	64	99.2	96.9
	128	99.3	97.2

PCA & FLD

Dimension Number(PCA)	Dimension Number (FLD)	Random Sampling		K-Fold Cross Validation	
		Hit Rate(%) at Left Ear	Hit Rate(%) at Right Ear	Hit Rate(%) at Left Ear	Hit Rate(%) at Right Ear
4	2	31.2	32.9	31.5	34
8	4	71.1	78.5	71.5	76.2
16	4	86.1	87.5	81.6	82.4
	8	96.3	98.1	92.3	94.7
32	4	89.9	89.8	86.4	87.3
	8	98.3	98.7	97.2	96.9
	16	99.3	100	98.3	99.4
64	4	92.4	90.2	88.5	87.1
	8	98.7	99.1	96.9	87.1
	16	99	99.6	98.3	98.3
	32	99.6	99.9	98.8	99.6
128	4	85.7	88	77.5	77.1
	8	97.6	98.1	92.6	94.3
	16	98.9	99.6	97.9	98.4
	32	99.2	99.8	98.3	99.1

DCVA

Ear Location	Dimension Number (Number of Feature Vectors)	Hit Rate (Random Sampling)	Hit Rate(K-Fold Cross validation)
Left	4	94	91
	8	98	97
	16	99.3	100
Right	4	91.3	96
	8	98.7	98.7
	16	100	100

4.CONCLUSION

Several recognition algorithms were introduced in the last two decades. According to the results that are presented in this thesis, 2D image based, linear recognition algorithms have better performance at ear recognition tasks than face recognition task that are presented in the literature previously. The explanation of this situation is conditions such as make up, illumination, posing, the rotation angle of face to up/down/right/left directions and emotional expressions such as smiling and frowning brows, mustache and beard do not affect ear as much as they affect face. PCA, FLD, DCVA and LPP are almost excellent at ear recognition tasks according to experiment have been done in this study. The experiments of error rate versus the numbers of selected dimensions show that error rate can be minimized by choosing adequate number of dimensions for representation of ear images. Four degrees of cropping applied to testing images to show effects of deformed test images.

The experiments showed that if the cropping ratio increases, error rate increases. Hit rate and cropping are inversely proportional. According to the experiment results, this thesis achieved its goal and showed that ear is adequate alternative to face for recognition tasks.

REFERENCES

[1] Karimi B., 2006. Comparative Analysis of Face Recognition Algorithms and Investigation on the Significance of Color, *M. Sc. Thesis,* Concordia University, Montreal, Quebec.

[2] Duda R. O., Hart P. E. and Stork D. G., 2001. Pattern Classification, John Wiley & Sons, Inc., New York.

[3] Turk M. A. and Pentland A. P., 1991. Face Recognition using Eigenfaces, *IEEE Conference on Computer Vision and Pattern Recognition*, pp.586-591

[4] Çevikalp H., Neamtu M., Wilkes M. and Barkana A, 2005. Discriminative Common Vectors for Face Recognition, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 27, no 1, pp. 4-13.

[5] He X., Yan S., Hu Y., Niyogi P. and Zhang H. J., 2005. Face Recognition Using Laplacianfaces, *IEEE Trans. On Pattern Analysis and Machine Intelligence,* vol. 27 no. 3, pp. 328-340.

[6] He X. and Niyogi P., 2003. Locality Preserving Projections, *Proc. Conf.Advances in Neural Information Processing Systems*.

[7] Chang K., Bowyer K. W., Sarkar S. and Victor B., 2003. Comparison and Combination of Ear and Face Images in Appearance-Based Biometrics, *IEEE Trans. On Pattern Analysis and Machine Intelligence,* vol. 25 no. 9, pp. 1160-1165.

[8] Victor B., Bowyer K. W. and Sarkar S., 2002. An Evaluation of Face and Ear Biometrics, *Proc. Int'l. Conf. Pattern Recognition*, pp. 429-432.

[9] Hurley D. J., Nixon M. S. and Carter J. N., 2005. Forced Field Feature Extraction for Ear Biometrics, *Computer Vision and Image Understanding,* 98, pp. 491-512.

[10] Choras M., 2005. Ear Biometrics Based on Geometrical Feature Extraction, *Electronic Letters on Computer Vision and Image Analysis,* 5(3), pp.84-95.

[11] Balaji, Prasanalakshmi and Kannammal, Biometric Methods - A Secure Survey (October 25, 2009). Available at SSRN: https://ssrn.com/abstract=1493905.

[12] S. M. S. Islam, M. Bennamoun, R. Owens, and R. Davies. Biometric approaches of 2d-3d ear and face: A survey. In T. Sobh, editor, Advances in Computer and Information Sciences and Engineering, pages 509–514. Springer Netherlands, 2008.

[13] M. Choras. Image feature extraction methods for ear biometrics–a survey. In Computer Information Systems and Industrial Management Applications, 2007. CISIM '07. 6th International Conference on, pages 261 –265, june 2007.

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

[15] H.-K. Lammi. Ear biometics. Technical report, Lappeenranta University of Technology, Department of Information Technology, 2004.

[16] R. Raghavendra, K. Raja, A. Pflug, B. Yang, and C. Busch. 3d face reconstruction and multimodal person identification from video captured using a smartphone camera. In Proceedings of the 13th IEEE Conference on Technologies for Homeland Security (HST), November 2013.

AUTHORS BIOGRAPHY

Ms. R. Parimala
Ph.D Research Scholar, Bharathiar University, Coimbatore, India
Assistant Professor, S.S.K.V College of Arts and Science for Women, Kanchipuram, India
Email : parimalasuresh80@gmail.com

Dr. C. Jayakumar
Ph.D Research Supervisor, Bharathiar University, Coimbatore, India
Professor, CSE Department, RMK Engineering College, Chennai, India
Email : cjayakumar2007@gmail.com