LBP-Based Ear Recognition

N. B. Boodoo-Jahangeer and S. Baichoo, University of Mauritius

Abstract— **The ear, as a biometric, has been given less attention, compared to other biometrics such as fingerprint, face and iris. Since it is a relatively new biometric, no commercial applications involving ear recognition are available. Intensive research in this field is thus required to determine the feasibility of this biometric. In medical field, especially in case of accidents and death, where face of patients cannot be recognized, the use of ear can be helpful. In this work, yet another method of recognizing people through their ears is presented. Local Binary Patterns (LBP) is used as features and the results are compared with that of Principal Components Analysis (PCA). LBP has a high discriminative power, tolerance against global illumination changes and low computational load. Experiments were done on the Indian Institute of Technology (IIT) Delhi ear image database and results show that LBP yields a recognition rate of 93 % while PCA gives only 85 %.**

INTRODUCTION

The increasing demand of robust security system has led to intensive research in biometrics. Biometric refers "to identifying an individual based on his or her distinguishing characteristics" [1]. Biometric traits are often classified as physiological or behavioral traits. Physiological characteristics are related to the shape of the body. Examples include, but are not limited to fingerprint, face, iris, hand geometry, palm print, retina and DNA. Behavioral characteristics are related to the behavior of a person, including but not limited to: Keystrokes, signature, gait, and voice.

Traditional methods, used to secure valuables and confidential information, include passwords, access cards, PIN codes, credit cards, keys and tokens. These methods however, are not very secure as they are easily transferable and quite easily obtained by any third parties who want unauthorized access to valuables and information [2]. Biometric-based methods easily deal with these problems since users are identified by who they are, not by something they have to remember or carry with them [3]. Biometric traits are more difficult to forge, copy, share, misplace or guess [4]. A biometric system requires the person being authenticated to be present at the time and point of authentication. Along with the rapid growing of this emerging technology, the system performance, such as accuracy and speed, is continuously improved.

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N. B. Boodoo-Jahangeer is a PhD student, at the University of Mauritius, pursuing research on face and ear recognition. (E-mail: nazmeen182@yahoo.com).

S. Baichoo is Associate Professor in the Department of Computer Science at the University of Mauritius. (E-mail: sbaichoo@uom.ac.mu).

Each biometric has its advantages and disadvantages. No single biometric is suitable for all applications. For example, fingerprint, though reliable, cannot be used in Surveillance applications since it requires the subject to participate in the authentication process. Extensive research is being done in different biometrics to determine their suitability for specific applications. This study focuses on the use of ear biometric for recognition.

Ear-based recognition is of particular interest because it is non-invasive, and because it is not affected by environmental factors such as mood, health, and clothing. Also, the appearance of the auricle (outer ear) is relatively unaffected by aging, making it better suited for long-term identification [5].

Ear images can be easily taken from a distance without knowledge of the person concerned. Therefore ear biometric is suitable for surveillance, security, access control and monitoring applications. Earprints, found on the crime scene, have been used as a proof in hundreds of cases in the Netherlands and the United States [6].

In this study, the use of Local Binary Pattern was investigated for Ear recognition. Though the use of DNA is available in hospital, it may take longer time to get the results of recognition since DNA tests involves chemical processes [7]. In such situations, ear can be useful for providing a rapid recognition rate where face of a patient may be injured and cannot be used for recognition purpose.

I. BACKGROUND STUDY

Ears have certain advantages over the more established biometrics; as Bertillon [8] pointed out, they have a rich and stable structure that is preserved from birth well into old age. The ear does not suffer from changes in facial expression, and is firmly fixed in the middle of the side of the head so that the immediate background is predictable, whereas face recognition usually requires the face to be captured against a controlled background. Ear image acquisition does not have an associated hygiene issue, as may be the case with direct contact fingerprint scanning, and is not likely to cause anxiety, as may happen with iris and retina measurements. The ear is large compared with the iris, retina, and fingerprint and therefore is more easily captured.

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Two studies performed by Iannarelli [9] provide enough evidence to show that ears are unique biometric traits. The first study compared over 10,000 ears drawn from a randomly selected sample in California, and the second study examined fraternal and identical twins, in which physiological features are known to be similar. The evidence from these studies supports the hypothesis that the ear contains unique physiological features, since in both studies all examined ears were found to be unique though identical twins were found to have similar, but not identical, ear structures especially in the Concha and lobe areas. Nejati H. et al. [10] has proved that identical twins can be identified from their ear images. Fig. 1 shows the anatomy of the ear.

The medical literature reports [9] that ear growth after the first four months of birth is proportional. It turns out that even though ear growth is proportional, gravity can cause the ear to undergo stretching in the vertical direction. The effect of this stretching is most pronounced in the lobe of the ear, and measurements show that the change is non-linear. The rate of stretching is approximately five times greater than normal during the period from four months to the age of eight, after which it is constant until around 70 when it again increases.

The main drawback of ear biometrics is that they are not usable when the ear of the subject is covered [9]. In case of active identification systems, this is not a drawback as the subject can pull his hair back and proceed with the authentication process. The problem arises during passive identification as in this case no assistance on the part of the subject can be assumed. In the case of the ear being only partially occluded by hair, it is possible to recognize the hair and segment it out of the image.

In this paper, the use of Local Binary Pattern (LBP) as features for ear recognition will be studied. A similar study was done by Burge and Burger [11]. The latter applied Local Binary Pattern(LPB) for face recognition and proved that it outperforms PCA-based face recognition.

Fig. 1:1 Helix Rim, 2 Lobule, 3 Antihelix, 4 Concha, 5 Tragus, 6 Antitragus, 7 Crus of Helix, 8 Triangular Fossa, 9 Incisure Intertragica [5].

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II. Methodology

There are several variations of LBP proposed in literature. Mäenpää and Pietikäinen [12] proposed an opponent color LBP, and investigated joint and separate use of color and texture in classification. Tan et al. [13] and Wang et al. [14] investigated the combination of the LBPs and Gabor features. A revised LBP was studied by Liao et al. [15], which make use of the most frequently occurred patterns of LBP to improve the recognition accuracy.

Heikkilä et al. [16] used a novel descriptor combining the strengths of SIFT (Scale Invariant Feature Transform) descriptor and LBP, in which center-symmetric local binary patterns (CS-LBP) were used to replace the gradient operator used by the SIFT operator. Heusch et al. have developed a preprocessing algorithm based on the LBPs to handle variations in illumination in a face authentication system [17]. The use of LBPs has also been considered in the recognition of actions by Kellokumpu et al. [18]. Wang et al. have investigated the use of LBPs in the facial age classification [14].

The LBP operator, originally introduced by Ojala et al. [19], is a powerful way of describing the texture of an image. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of $2^8 = 256$ different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood.

The steps for LBP operator are given into more details below:
The image is first divided into cells, consisting of a number of 3 × 3 pixel blocks. The center pixel, px_c, in a block is compared to each of its 8 neighbors, px_i (i=0, 1, …,7). The pixels are followed along a circle, either clockwise or counter-clockwise.

$$LB(px_i - px_c) = \begin{cases} 1, & px_i \geq px_c \\ 0, & px_i < px_c \end{cases}$$

Where the center pixel's value is greater than the neighbor's value, "0" is written. Otherwise, "1" is written. This gives an 8-digit binary number. Fig. 2 illustrates the basic LBP operator.

82	98	100
81	85	94
88	87	84

Threshold

0	1	1
0		1
1	1	0

Fig. 2: Basic of LBP,(a) Gray Value, (b) Corresponding Binary Pattern

Then, the values of the pixels in the thresholded neighborhood are multiplied by the weights given to the corresponding pixels. Finally, the values of the eight pixels are summed to obtain the LBP number for the centre pixel:

$$LBP = \sum_{i=0}^{7} LB(px_i - px_c) \cdot 2^i$$

The LBP number derived is 110 (2 + 4 + 8 + 32 + 64), as shown in Fig. 3. The histogram, over the cell, of the frequency of each "number" occurring is computed. The histograms of all cells in the image are then concatenated. This gives the feature vector for the image.

Multiply

0	1	1
0		1
1	1	0

1	2	4
128		8
64	32	16

0	2	4
0		8
64	32	0

Fig. 3: LBP number calculation

Fig. 4 shows a sample image and the corresponding histogram.

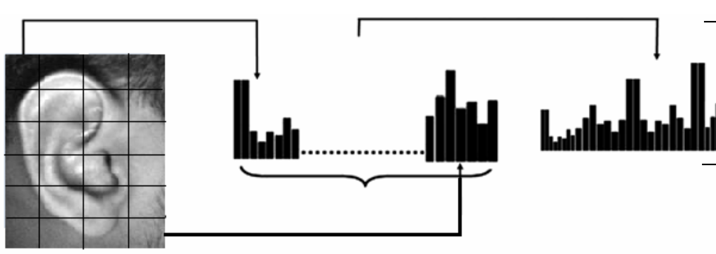

Fig. 4: Image and histograms

For the purpose of comparison, the Principal components analysis (PCA) technique, as described by Turk and Pentland [20] was implemented. PCA is a technique most commonly used for dimensionality reduction in computer vision. The features extracted are based on Karhunen-Loeve (KL) expansion [20]. The corresponding algorithm in the context of face recognition is called eigenface method. In fact, the eigenface method generates features that capture the holistic nature of the faces through PCA.

The high dimensional space with all the eigenfaces is called the image space (feature space). Also, each image is actually a linear combination of the eigenfaces. The amount of overall variation that one eigenface counts for, is actually known by the eigenvalue associated with the corresponding eigenvector. If the eigenface with small eigenvalues are neglected, then an image can be a linear combination of reduced no of these eigenfaces. For example, if there are M images in the training set, we would get M eigenfaces. Out of these, only M' eigenfaces are selected such that they are associated with the largest eigenvalues. These would span the M'-dimensional subspace 'face space' out of all the possible images (image space).

When the face image to be recognized (known or unknown), is projected on this face space , we get the weights associated with the eigenfaces, that linearly approximate the face or can be used to reconstruct the face. Now these weights are compared with the weights of the known face images so that it can be recognized as a known face in used in the training set. In simpler words, the Euclidean distance between the image projection and known projections is calculated; the face image is then classified as one of the faces with minimum Euclidean distance.

III. DATASET

The Indian Institute of Technology (IIT) Delhi ear image database [21] was used for the purpose of this research. The IIT Delhi ear image database was acquired from 125 different subjects and each subject has at least 3 ear images. All the subjects in the database are in the age group 14-58 years. The resolution of these ear images is 272 x 204 pixels. Since different subjects have different number of images in the database, subjects having five images in the database were selected. The training set consisted of 3 images per subject and the test set consisted of two images per subject. Fig. 5 shows the sample ear images from the database.

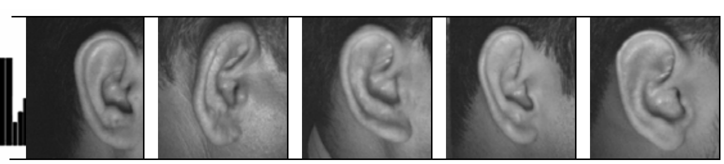

Fig. 5: Sample Ear Images

IV. RESULTS

To measure the performance of the system, the recognition rate, the False Acceptance Rate (FAR) and False Rejection Rate (FRR) were calculated. The experimental results are shown in Table 1 below:

As shown in Table 1, the Linear Binary Pattern (LBP) method yielded a recognition rate of 93 % as compared to the Principal Components Analysis (PCA) that gave a recognition rate of 85 %. The LBP method has lower FAR and FRR values. A Low FAR indicates that there will be fewer imposters accepted in the system while a low FRR implies that fewer authorized users will be rejected by the system.

The difference of the results can be explained by the fact that local binary patterns captures the variance between pixel intensities, thus has more accurate information whereas PCA loses part of information during its dimensionality reduction. The result obtained in this investigation is in line with other research works that demonstrate LBP features yield better performance than PCA [22] [23].

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V. CONCLUSION

The use of Ear for recognition has been investigated in this paper. This technique can be used to identify patients having severe face injuries making face recognition impossible. A new method, Local Binary Pattern (LBP), was applied to extract the histogram of each cell based on their neighborhood's pixel intensities. The histograms were concatenated and used as features for matching. This technique was tested on the IIT Delhi Ear database and a recognition rate of 93 % was obtained when compared to the benchmark algorithm, PCA, which yielded a recognition rate of 85 % only. Such type of recognition system can be used either standalone or can be fused with an existing face recognition system. The use of the LBP operator for recognition needs to be further investigated, its effectiveness in a multi-model environment, whether the number of sub-regions affects system performance, and testing LBP in uncontrolled environments.

TABLE I. EXPERIMENTAL RESULTS

	Recognition Rate	FAR	FRR
PCA	85%	0.4	0.2
LBP operator	93%	0.2	0.07

VI. REFERENCES

[1] B. Bolle, R. M., Connell, J. H., Pankanti, S., Ratha, N. K. & Senior, A. W., 2003. Guide to Biometric: Springer-Verlag, New-York.

[2] Jain, A., Ross, A., Prabhakar, S. (2001), Fingerprint Matching Using Minutiae and Texture Features. In: Proceedings of the International Conference on Image Processing, pp 282-285, Thessaloniki, Greece.

[3] Choraś, M., 2005. Ear Biometrics Based on Geometrical Feature Extraction, Electronic Letters on Computer Vision and Image Analysis, Vol. 5, No. 3, pp. 84-95.

[4] Pankanti, S. & Jain, A. K. 2008, Beyond Fingerprinting, Scientific American, pp. 78-81.

[5] M. Saleh, S. Fahmi, and L. Abbott "Using Ears as a Biometric for Human Recognition", 16th International Conference on Computer Theory and Applications (ICCTA 2006), Alexandria, Egypt, pp. 311-314, Sept. 2006.

[6] A. J. Hoogstrate, H. Heuvel Van Den, and E. Huyben, "Ear Identification Based on Surveillance Camera's Images", Netherlands Forensic Institute, 2000.

[7] N. James, "DNA Testing in Criminal Justice: Background, Current Law, Grants, and Issues" Dec 2012, Congressional Research Service, Available at: http://www.fas.org/sgp/crs/misc/R41800.pdf, Retrieved on 26th July 2013.

[8] A. Bertillon, "La photographie judiciaire, avec un appendice sur la classification et l'identification anthropométriques", Gauthier-Villars, Paris, 1890.

[9] A. Iannarelli, "Ear Identification". Forensic Identification Series. Paramont Publishing Company, Fremont, California, 1989.

[10] H. Nejatiy, L. Zhang, T. Sim, E. Martinez-Marroquin1z, G. Dong, "Wonder ears: Identification of identical twins from ear images", 2012 21st International Conference on Pattern Recognition (ICPR), Tsukuba, pp. 1201 - 1204, 2012.

[11] M. Burge and W. Burger, "Ear Biometrics in Computer Vision", International Conference on Pattern Recognition 2000, pp. 822 – 826.

[12] T. Mäenpää M. and Pietikäinen, "Classification with Color and Texture: Jointly or Separately?", Pattern Recognition 37(8):1629-1640, 2004

[13] X. Tan and B. Triggs, "Fusing Gabor and LBP feature Sets for Kernel-based Face Recognition", Proceedings of the IEEE International Workshop on Analysis and Modeling of Face and Gesture, pp.235-249, 2007.

[14] J. G. Wang, W. Y. Yau and H. L. Wang, "Age Categorization via ECOC with Fused Gabor and LBP Features". Proceedings of the IEEE Workshop on Applications of Computer Vision (WACV), pp.313-318, 2009.

[15] S. Liao, M.W.K. Law and A.C.S. Chung, "Dominant Local Binary Patterns for Texture Classification". IEEE Trans. Image Processing 18(5):1107-1118, 2009.

[16] M. Heikkilä, M., Pietikäinen and C. Schmid, "Description of Interest Regions with Local Binary Patterns". Pattern Recognition 42(3):425-436, 2009.

[17] G. Heusch, Y. Rodriguez and S. Marcel, "Local Binary Patterns as an Image Processing for Face Authentication", Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition, pp. 6-14, 2006

[18] V. Kellokumpu, G. Zhao, and M. Pietikäinen, "Recognition of Human Actions Using Texture Descriptors". Machine Vision and Applications, vol. 22, no. 5, pp. 767-780, 2010

[19] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on featured distribution," Pattern Recognition, vol. 29, no. 1, 51–59, 1996.

[20] M. Turk and A. Pentland, "Eigenfaces for Recognition," Journal of Cognitive Neuroscience, vol. 3, pp. 71-86, 1991.

[21] A. Kumar and C. Wu, "Automated Ear Identification using Ear Imaging," Pattern Recognition, vol. 45, no. 3, pp.956-968, March 2012.

[22] O. Nikisins, and M. Greitans, "Reduced complexity automatic face recognition algorithm based on Local Binary Patterns", 2012 19th International Conference on Systems, Signals and Image Processing (IWSSIP), 2012, pp. 433 – 436.

[23] C. Liu, J. Lu and L. Li, "Three-level face features for face recognition based on center-symmetric Local Binary Pattern, 2011 IEEE International Conference on Computer Science and Automation Engineering (CSAE), 2011, pp. 394 – 398.