IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Vol.-6, Special Issue-7, Sept. 2018 E-ISSN: 2347-2693

A Review on Texture Descriptors in 2D Ear Recognition

Resmi K R[1*], G Raju[2]

[1]School of Computer Science Mahatma Gandhi University Kottayam, Kerala, India
[2]Dept. of Computer Science and Engineering, Faculty Of Engineering Christ Deemed To Be University Bangalore, India

*Corresponding Author: resmykr@gmail.com

Available online at: www.ijcseonline.org

Abstract— Ear recognition is an active area of research and automatic ear recognition is one of the challenging areas in biometric and forensic domains. Human ear contains large amount of unique features for recognition of an individual. There are different approaches and descriptors that achieve relatively good results in ear biometric recognition. Studies show that there is poor recognition performance in case of occlusion, illumination variation and pose variation. This paper presents an overview of different local texture descriptors in the field of automatic ear recognition. The local descriptors which calculate features from small local patches have proven to be more effective in real world situations compared to the global descriptors which extract features from whole image.

***Keywords*—**Ear, Biometric, Texture Descriptors, Feature Extraction, LBP, GLCM, LPQ

I. INTRODUCTION

The principle idea behind biometric is the verification or identification of a person based on unique characteristics. Biometric system mainly uses physiological and behavioral characteristics for the recognition of an individual. Ear, a physiological biometric is used as a major Biometric Trait in forensic applications. The external anatomy of an ear [1] is shown in Fig. 1. The structural patterns like helix, lobe, concha, crus of helix etc. differ in shape, relative position, and appearance from person to person. Ear have certain benefits compared to other biometric modalities. According to medical reports [2] the structure of an ear is stable in the age group between 8 to 70. Ear does not change with expressions unlike face biometric [3]. Ear is a contactless biometric and it is immune from hygiene problem that occur in contact biometric like iris, retina etc. Ears smaller size and more uniform color distribution make it faster to work. More over ear biometric is now a day used with other biometric traits in multimodal system [4].The main problems with ear biometric is occlusion with hair, ear ring, spex, and ear phones.

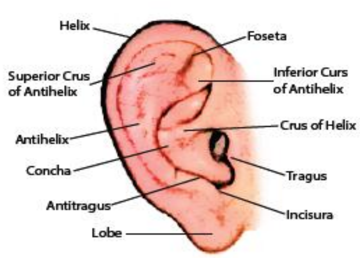

Fig. 1. External Ear and its parts.

A typical ear recognition system consists of three main steps: ear normalization, feature extraction and classification. Ear normalization mainly normalizes the ear image in to a standard size. The feature extraction module extract features from ear and helps to design an effective classifier for recognition. Majority of ear biometric research is in feature extraction and classification. In real scenario, a big obstacle for ear recognition is to find an effective descriptor to represent the ear structure, which can be affected by change in illumination, pose, noise and occlusion.

This paper mainly concentrates on the type of feature extraction techniques used in 2D ear recognition. Local descriptors which extract features from small local areas of ear structure have proven to be more effective than global descriptors which use ear structure as whole. In this paper, a detailed survey on the local texture descriptors for 2D ear recognition is presented.

The rest of the paper is organized as follows. Section II discusses the related works on ear recognition. Section III contains important local texture descriptors used in ear biometric followed by discussion and conclusion in section IV.

II. RELATED WORKS

The French criminologist Alphonse Bertillon [5] is considered to be the first to have suggested the possible use of ear as a means of personal identification as part of his new scientific method of criminal identification .Alfred Iannarelli

[2] developed the first system for ear classification based on 12 manual measurements. This system played an important role in forensic science for many years in United States.

Depending on the feature extraction techniques, 2D ear recognition is classified into geometric/statistical, local, holistic/global and hybrid approaches. Geometric techniques uses ear geometric features such as shapes, curve and relations between ear parts. Early works on ear biometrics is based on geometric features. Burge and Burger [6] developed the first computerized system based on geometric approach. They used graph matching algorithm based on vornoi diagram of curves from extracted contours. Moreno et al.[7] developed an ear recognition system based on geometric features such as ear shape and wrinkles. Mu et al [8]and Choras [9] also used geometric features for their classification. Geometric methods are not effective in situations such as poor quality image, occlusion, lighting and pose.

Holistic techniques such as principal component analysis(PCA), Force Field Transform, independent component analysis etc. extract features from the ear structure as a whole. Hurley et al.[10] developed one popular approach for ear recognition which used force field transformation. This technique calculate the force field from input ear image by treating pixels as Gaussian force field. Victor et al[11] and Chang et al. [12] used PCA for ear recognition. PCA is used for dimensionality reduction. Zang et al.[13] developed a system with ICA feature and a neural network for classification. Compared to PCA, their system achieved a better rank-1 recognition rate.

Currently lots of works in ear biometric is based on image texture features. Texture analysis is a local descriptor which extracts features from local areas of ear structure. Nanni and lumni [14] extracted gabor features from the selected color spaces. They achieved a rank -1 recognition rate of 84 % on UND E database. Pflug et al.[15] used local phase quantization features(LPQ) alone for texture extraction and achieved a rank - 1 recognition rate of 93.1%. Benzaoui et al. [16] used binarized statistical image features(BSIF)which is a 256bin dense descriptor where a binary code is generated by convolving a filter trained by independent component analysis. Gray level co-occurrence matrix(GLCM) and Local binary patterns(LBP) are texture descriptors that are computationally simple compared to gabor features which are computationally more demanding. Pflug et al. [17] used a hybrid technique by combining different texture features like LPQ,BSIF,LBP and HOG. They achieved a better recognition rate when compared to their previous work which uses LPQ alone. Jacob and Raju [18] conducted experiments on IITD II database by combining features like GLCM,LBP and gabor filter with rank- 1 recognition rate 94.1%.However, hybrid approaches are computationally complex than simple holistic or local technique.

III. LOCAL TEXTURE DESCRIPTORS

Texture is the characteristic appearance of objects given by shape, size, density, arrangement etc. Local texture descriptors extract low level features that are used to describe content in an image in addition to color features. The following are some of the important texture descriptors used in ear biometrics.

A.Gra- Level Co-Occurence Matrix

GLCM is one of the most important technique used in texture feature extraction. GLCM is actually a matrix which describe how often different combinations of gray level co-occur in an image. GLCM calculate image properties based on second order statistics. Fig. 2 shows calculation of GLCM from input image f.

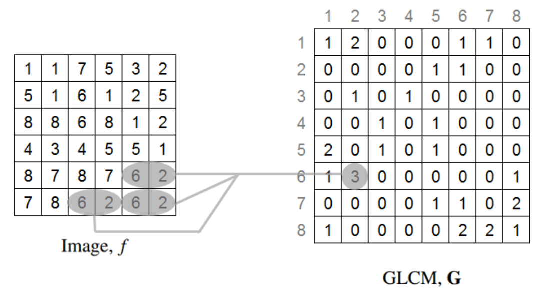

Fig. 2. An example of calculating a Gray Level Co-occurrence Matrix.

GLCM is a matrix that is obtained from input image f, which consists of N rows and N columns where N is the number of gray levels in f. The entry (i,j) in GLCM matrix represents the number of times the pair of gray levels i occurred in the specified spatial relationship (by default pixel of interest and its immediate right) to a pixel with value *j* occur in the original image. Statistical features like correlation, contrast, homogeneity, shade, entropy are then extracted from this matrix. The four widely used GLCM features in literature are contrast, correlation, energy and Homogeneity.

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i-j)^2 \qquad (2)$$

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij}$$

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$$

B.Local Binary pattern(LBP)

The LBP operator introduced by Ojala et al. [19] is a gray scale invariant texture descriptor. It is a simple and very effective texture descriptor which calculates the LBP code for each pixel and then the histogram of these codes can be used as texture local descriptor. The original LBP operator take 3x3 neighbourhood of each pixel and then threshold it based on the central value and consider the result as a binary number. In thresholding, 1 is used if the central pixel value is less than neighbour's value and 0 otherwise. Then multiply the threshold binary mask with predefined mask, which is usually an incremental power of two and summing the values to obtain the 8 bit LBP Code. The LBP code generation is shown in Fig. 3.

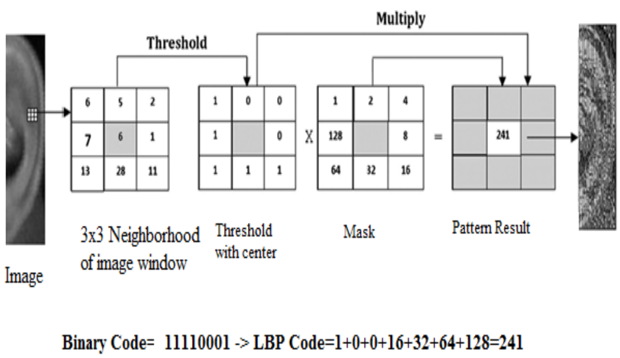

Fig. 3. Calculation Of LBP operator applied on normalized ear image from IITD database.

The LBP operator can use any circular neighbourhood where each LBP code can be regarded as microtexton. The notation (P,R) is generally used for pixel neighbourhood where P is the set of sampling points on a circle of radius R as shown in Fig. 4. For pixel (X_c, Y_c) the value of LBP code[19] is given by the equation 5 .

$$\mathrm{LBP}^{P,R}(x_c, y_c) = \sum_{i=1}^{P} S(g_i^{P,R} - g_c)2^{i-1}, \quad (5)$$

$S(x)$ is defined as $S(x) = \begin{cases} 1 & \text{if } x \geq 0; \\ 0 & \text{otherwise;} \end{cases}$

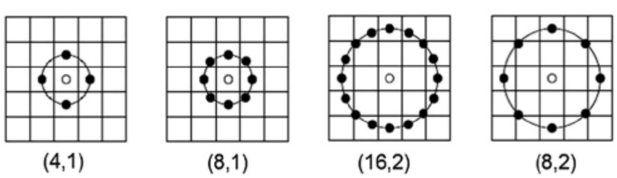

Fig. 4. Neighborhood set of Different(P,R)

The LBP code in an image is collected as histogram. For efficient representation the image is first divided in to different blocks from which local LBP histogram is extracted to build local image descriptor. The local histograms are then concatenated to form a global histogram which contains global description. LBP is powerful by its computational simplicity and discriminative power.

C. Local Phase Quantization(LPQ)

An LPQ descriptor was proposed by Ojansivu and Heikkil [20] to solve the relative sensitivity of LBP to blur. In LPQ an image is transformed into a Fourier domain and only phase information is used in subsequent steps. The LPQ calculation is as follows. For each pixel in an image the phase within the predefined radius is calculated and image quantization is performed by taking the sign of both real and imaginary part of the local phase. Similar to LBP, an 8 bit code is generated by quantized neighbourhood of each pixel. The image is divided into fixed blocks in LPQ. Then local LPQ histogram features are computed within each region. .The local histograms are then concatenated to form a global feature histogram. An LPQ method performs well with images having serious motion blur and deformation.

D. Binarized Statistical Image features(BSIF)

Inspired by LBP and LPQ, Kannala and Rahtu [21] proposed BSIF for texture classification. BSIF uses a fixed set of filters learned from a small set of natural images and then binary code is generated by convolving the image with these filters. Each bit in the code is associated to a particular filter. The number of bits determines the number of filters used. It is called BSIF because the statistical feature of natural patches determines the descriptor. Like LBP and LPQ, a histogram from mapped values is created in BSIF image. The key idea in BSIF is learning instead of tuning, to get statistically meaningful data.

E.Local Directional pattern(LDP)

LDP is an 8 bit binary code assigned to each pixel in an image similar to LBP. Here, the binary pattern is calculated by comparing the edge response value of a pixel in different direction. Kirsch masks with 8 different orientations centered on its own position to calculate 8 directional edge response value m0 to m7. Inorder to generate LDP ,take the most K prominent directions and remaining bit as zeros. The LDP code is more stable in presence of noise and non-monotonic illumination changes compared to LBP because LDP generate gradients which is more stable than gray scale value. (6) The 8 Kirsch mask with 8 different directions is shown in Fig. 5.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$\text{East } M_0 \qquad \text{North East } M_1 \qquad \text{North } M_2 \qquad \text{North West } M_3$$

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

$$\text{West } M_4 \qquad \text{South West } M_5 \qquad \text{South } M_6 \qquad \text{South East } M_7$$

Fig. 5. Kirsch edge response mask in 8 directions

F.Gabor Filter

It is a linear filter used for texture analysis. It basically analyzes whether there is any frequency component in a region or a point under analysis. Gabor filter gives higher responses at edges and places where texture changes. Most of the Gabor related features depend on Gabor filter banks in which several filters are applied simultaneously in to an input image.

IV. DISCUSSION AND CONCLUSION

Table 1 shows recognition rates of different feature extraction techniques on IIT Delhi databases. From the table, it is clear that most of the current works in ear biometric is based on local texture features and it achieves high recognition rates.

TABLE 1.RECOGNITION RATE OF DIFFERENT METHODS ON IITD DATABASE

Reference	*Method*	*Dataset*	*#sub*	*Recognition R1(%)*
2012,chan and Kumar [22]	2D Quadrature Filter	IITD I IITD II	125 221	96.5 96.1
2011,Kumar and Wu [3]	Orthogonal Log Gabor Filter Pairs	IITD II	221	95.9
2013,Kumar and Chan [23]	SRC of Local Grey-level Orientations	IITD I IITD II	125 221	97.1 97.7
2014,Basit and Shoaib [24]	Non-Linear Curvelet Features	IITD II	221	96.2
2014,Benzaoui et al. [25]	BSIF	IITD II	221	97.3
2014, Jacob and Raju [18]	Gray Level Co-Occurance+LBP+Gabor Filter	IITD II	221	94.1
2015,Benzaoui et al. [26]	LBP and Haar wavelet Transform	IITD	121	94.5
2015,Benzaoui et al. [27]	BSIF	IITD I IITD II	125 221	96.7 97.3
2015,Bourouba et al. [28]	Multi-Bags-Of-Features Histogram	IITD I	125	96.3
2015,Meraoumia et al. [29]	Gabor filters	IITD II	221	92.4
2016,Youbi et a1. [30]	Multiscale LBP descriptor and KL divergence	IITD I	125	95.02
2017,Benzaoui et al. [31]	BSIF+anatomical and embryological information	IITD I IITD II	125 221	97.39 97.63

Texture feature extraction techniques which were originally used in face recognition or other computer vision tasks can also be applied for ear recognition. This paper discussed the important texture descriptors in 2D ear recognition. The local descriptors which operates on local patterns is found to give good results compared to global descriptors which extracts features from image as a whole. The hybrid approach by combining different texture features gives better recognition results compares to single feature alone.

REFERENCES

[1] Ear biometrics: A survey of detection, Emersic, Z., Struc, V., & Peer, P. (2017). Ear recognition: More than a survey. Neurocomputing, 255, 26-39.

[2] A. Iannarelli. Ear identification. Forensic Identification Series. Paramont publishing company, Fremont,California,1989.

[3] A. Kumar, C. Wu, Automated human identification using ear imaging, Pattern Recognition(2011) ,doi:10.1016/j.patcog.2011.06.005 .

[4] Choras M. (2004) Human Ear Identification Based on Image Analysis. In: Rutkowski L., Siekmann J.H., Tadeusiewicz R., Zadeh L.A. (eds) Artificial Intelligence and Soft Computing - ICAISC 2004. ICAISC 2004. Lecture Notes in Computer Science, vol 3070. Springer, Berlin, Heidelberg..

[5] Bertillon A. Identification Anthropometrique: Instructions Signaletique; 1885.

[6] M. Burge, W. Burger, Biometrics: Personal Identification in Networked Society, Springer US, Boston, MA, 1996, Ch. Ear Biometrics, pp. 273–285.

[7] B. Moreno, A. Sánchez, J. F. Vélez, On the use of outer ear images for personal identification in security applications, in: Proceedings of the International Carnahan Conference on Security Technology, IEEE, 1999, pp. 469–476.

[8] Z. Mu, L. Yuan, Z. Xu, D. Xi, S. Qi, Shape and structural feature based ear recognition, in: Advances in biometric person authentication, Springer, 2004, pp. 663–670.

[9] M. Choras, R. S. Choras, Geometrical algorithms of ear contour shape representation and feature extraction, in: Proceedings of the International Conference on Intelligent Systems Design and Applications, IEEE, 2006, pp. 451–456.

[10] D. J. Hurley, M. S. Nixon, J. N. Carter, Automatic ear recognition by force field transformations, in: Proceedings of the Colloquium on Visual Biometrics, IET, 2000, pp. 7–1.

[11] B. Victor, K. Bowyer, S. Sarkar, An evaluation of face and ear biometrics, in: Proceedings of the International Conference on Pattern Recognition, Vol. 1, IEEE, 2002, pp. 429–432.

[12] K. Chang, K. W. Bowyer, S. Sarkar, B. Victor, Comparison and combination of ear and face images in appearance-based biometrics, Transactions on Pattern Analysis and Machine Intelligence 25 (9) (2003) 1160–1165.

[13] H.-J. Zhang, Z.-C. Mu, W. Qu, L.-M. Liu, C.-Y. Zhang, A novel approach for ear recognition based on ICA and RBF network, in: Proceedings of the International Conference on Machine Learning and Cybernetics, Vol. 7, IEEE, 2005, pp. 4511–4515.

[14] L. Nanni, A. Lumini, Fusion of color spaces for ear authentication,Pattern Recognition 42 (9) (2009) 1906–1913.

[15] A. Pflug, C. Busch, A. Ross, 2D ear classification based on unsupervised clustering, in: Proceedings of the International Joint Conference on Biometrics, IEEE, 2014, pp. 1–8.

[16] A. Benzaoui, N. Hezil, A. Boukrouche, Identity recognition based on the external shape of the human ear, in: Proceedings of the International Conference on Applied Research in Computer Science and Engineering, IEEE, 2015, pp. 1–5.

[17] A. Pflug, P. N. Paul, C. Busch, A comparative study on texture and surface descriptors for ear biometrics, in: Proceedings of the International Carnahan Conference on Security Technology, IEEE, 2014, pp. 1–6.

[18] L. Jacob, G. Raju, Advances in Signal Processing and Intelligent Recognition Systems, Springer International Publishing,Cham, 2014, Ch. Ear Recognition Using Texture Features – A Novel Approach, pp. 1–12.

[19] Ojala, T. and Pietikäinen, M. (1999), Unsupervised Texture Segmentation Using Feature Distributions. Pattern Recognition 32:477-486.

[20] V. Ojansivu and J. Heikkil, “Blur insensitive texture classification using local phase quantization,” in Proc. 3rd Int. Conf. on Image and SignalProcessing (ICSIP), pp. 236–243, Springer–Verlag, Berlin, Heidelberg(2008).

[21] J. Kannala and E. Rahtu, “BSIF: binarized statistical image features,” inProc. IEEE Int. Conf. on Pattern Recognition (ICPR), pp. 1363–1366,IEEE, Tsukuba, Japan (2012).

[22] T.-S. Chan, A. Kumar, Reliable ear identification using 2-D quadrature filters, Pattern Recognition Letters 33 (14) (2012)1870–1881.

[23] A. Kumar, T.-S. T. Chan, Robust ear identification using sparse representation of local texture descriptors, Pattern recognition 46 (1) (2013) 73–85.

[24] A. Basit, M. Shoaib, A human ear recognition method using nonlinear curvelet feature subspace, International Journal of Computer Mathematics 91 (3) (2014) 616–624.

[25] A. Benzaoui, A. Hadid, A. Boukrouche, Ear biometric recognition using local texture descriptors, Journal of Electronic Imaging 23 (5) (2014) 053008.

[26] A. Benzaoui, A. Kheider, A. Boukrouche, Ear description and recognition using ELBP and wavelets, in: Proceedings of the International Conference on Applied Research in Computer Science and Engineering, 2015, pp. 1–6.

[27] A. Benzaoui, N. Hezil, A. Boukrouche, Identity recognition based on the external shape of the human ear, in: Proceedings of the International Conference on Applied Research in Computer Science and Engineering, IEEE, 2015, pp. 1–5.

[28] H. Bourouba, H. Doghmane, A. Benzaoui, A. H. Boukrouche, Ear recognition based on Multi-bags-of-features histogram,in: Proceedings of the International Conference on Control,Engineering Information Technology, 2015, pp. 1–6.

[29] A. Meraoumia, S. Chitroub, A. Bouridane, An automated ear identification system using Gabor filter responses, in: Proceedings of the International Conference on New Circuits and Systems, IEEE, 2015, pp. 1–4.

[30] Z. Youbi et al., “Human ear recognition based on multi-scale local binary pattern descriptor and KL divergence,” in Proc. of the 39th IEEE Int. Conf. on Telecommunications and Signal Processing (TSP), pp. 685–688 (2016).

[31] Amir Benzaoui, InsafAdjabi, AbdelhaniBoukrouche, “Experiments and improvements of ear recognition based on local texture descriptors,” Opt. Eng. 56(4), 043109 (2017).

