

A Survey Paper on Human Identification using Ear Biometrics

Devesh Narayan, Sipi Dubey

Abstract— Human identification is about verifying a people for accessing information or permitting to enter in a restricted zone. Using ear as biometric tool has benefits involved in it; subjects never participate actively in the identification or verification process. Ear biometric finds its applications in the crime investigation, stopping ATM fraudulent and prevention of small baby swapping and mixing them in hospitals. This paper gives a detailed overview of different technical approaches that have been implemented for identifying subjects. Our survey provides good future prospects for the upcoming researchers in the field of ear biometric.

Index Terms— Ear Biometric, identification, verification

I. INTRODUCTION

The presence of loop-holes in almost all the conventional security system has forced the researcher to switch towards the ear biometrics system. The prime reasons behind their inclination are due to the presence of all the properties i.e. universality, uniqueness, permanence and collectable in nature in ear biometric. Also ears are not variable in its appearance during the change in pose and facial expressions. Alphonse Bertillon was the first individual to unveil the power of ear biometric for recognizing the criminal in jail [1]. Ear has a reputation of stable biometric feature that does not vary with time. Research also shows the evidence that slight ear size variation do happen as the person ages. Generally, this happens due to the sagging nature of the skin and muscles as person ages. Nixon studies reveal that recognition rate is not affected by aging [2].

In this paper, we start with discussing the anatomy of human ear, freely available ear database, different method used in ear recognition, the problem faced in ear biometrics and the applications related to it.

II. ANATOMY OF HUMAN EAR

The Figure 1. shows the specimen anatomy of a external human ear. It is also called by a name auricle or pinna. The important milestone of an external ear is shown in the figure 1. The detailed description of human ear is described as follows.

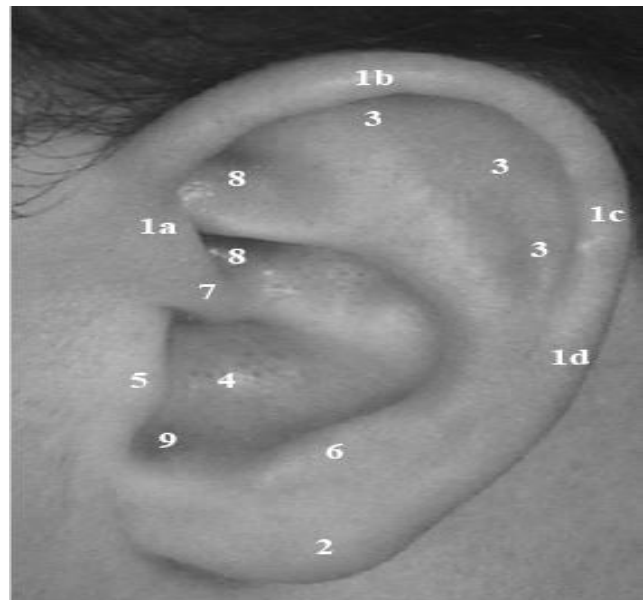


Figure 1. Anatomy of Human Ear

- 1 Helix Rim:** The prominent rim of the auricula is called the helix.
- 1a. Helix Root:** The transverse ridge of the helix continuing backward into the ear cavity.
- 1b. Helix lobe-notch:** The depression between the helix and the posterior border of the ear lobe, at the lower border of the helix (the helix cauda).
- 1c. Helix Tubercle:** A tiny bump at the lateral–superior aspect of the helix.
- 1d. Helix Cauda:** The lower border of the helix where it meets the lobe.
- 2. Lobule:** The human earlobe is composed of tough areolar and adipose connective tissues, lacking the firmness and elasticity of the rest of the pinna.
- 3. Antihelix:** On the pinna, a curved prominence of cartilage, parallel with and in front of the helix, is called the antihelix.
- 4. Concha:** The deepest depression in the auricle, called the concha, leads to the external auditory canal or meatus.
- 5. Tragus:** The tragus is a small pointed eminence of the external ear, situated in front of the concha, and projecting backward over the meatus.
- 6. Antitragus:** The antitragus is a feature of mammalian ear anatomy. In humans, it is a small tubercle that points interiorly, but it may be much larger in some other species.
- 7. Crus of Helix:** Crus of the helix is just above the tragus.

Manuscript Received on September 2014.

Prof. Devesh Narayan, Department of CSE, Rungta College of Engineering & Technology, Bhilai, India.

Dr. Sipi Dubey, Department of CSE, Rungta College of Engineering & Technology, Bhilai, India.

8. Triangular Fossa: The triangular depression between the two crura of the antihelix.

9. Incisure Intertragica: The deep notch in the lower part of the auricle between the tragus and antitragus.

III. EAR DATABASE

Many university and organization provides a collection of ear images databases. Their main objective is to support research efforts in ear biometrics. In the current section, we provide a view for the freely available ear databases to enhance the research activities in this field.

IIT Delhi Ear Database

The IIT Delhi database of an ear image is gathered by taking the snaps of students and staff ear present in the campus. The acquisition of an image was done during Oct 2006 – Jun 2007 using simple imaging set up. The age group of the subjects are in between 14 – 58 years. The resolution of an image is 272 x 204 pixels in jpeg format [3]. The database is available at http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Databases_Ear.htm. The sample images are shown in the Figure 2.



Figure 2. Sample Image from IIT Delhi Database

IIT Kanpur Ear Database

It consists of two sets of data i.e. Dataset -1 and Dataset-2. Data Set 1 has 801 side face images acquired from 190 subjects. Data Set 2 has again 801 side face images collected from 89 subjects. It consists of frontal view of the ears captured at three positions, first when a person is looking straight, second when a person is looking approximately 20 degrees down and third when a person is looking approximately 20 degrees up [4].

AMI Ear Database

An ear database from Mathematical Analysis of Images (AMI) is given for free usage in scientific applications to achieve ear identification. The database was created by Esther Gonzalez. All the images have been taken in an indoor environment. The database was acquired from 100 different subjects, having the age range of 19-65 years. For each individual, seven images (six right ear images and one left ear image) were taken. The resolution of these images is 492 x 702 pixels in jpeg format. The sample images are shown in the Figure 3.



Figure 3. Sample Image from AMI Database

USTB Ear Database

It is provided by Ear Recognition Laboratory at University of Science & Technology, Beijing [5]. They have created four databases - I, II, III and IV.

Database –I Every subject is photographed three different images. They are normal frontal image, frontal image with trivial angle rotation and image under different lighting condition. Each of them has 256 gray scales. Images had already experienced rotation and shearing.

Database –II The subject's head in right hand view is photographed by CCD camera. The distance between subject and camera is fixed to 2 meters.

Database –III All images are right side profile full images which are photographed with color CCD camera under the white background and constant lighting. The distance between camera and subject is 1.5 meters. The resolution of image is 768*576, 24-bit true color. Define the angle when CCD camera is perpendicular to ear as 0 degree, which we call profile side.

UND Ear Database

The University of Notre Dame (UND) ear databases are available free of cost [6]. The following are the collections that can be used for ear biometrics.

—Collection E. 464 different visible-light face side profile (ear) images from 114 human subjects.

Collection F. 942 different 3D and corresponding 2D profile (ear) images from 302 human subjects.

—Collection G. 738 different 3D and corresponding 2D profile (ear) images from 235 human subjects.

—Collection J2. 1800 different 3D and corresponding 2D profile (ear) images from 415 human subjects [7]

UBEAR Ear Database

The UBEAR database is acquired in uncontrolled environments [8]. The images are acquired when the subjects are moving and without any concern related to occlusions of the ears with subject hairs and poses. The objective behind this is to generate data sets which are robust biometric recognition systems. The UBEAR database has over 4 430 images and is growing with time.

IV. DIFFERENT METHODS USED IN EAR RECOGNITION

In this section, we made a survey only on 2D ear recognition techniques. In the 2D ear recognition techniques, basically a researcher focuses on finding the methods for extracting features present in the subject image. Then, subject image is compared with stored feature vector database. We have also found that following landmarks in the ear recognition techniques has been achieved.

Burge and Burger [9], transformed the subject ear into the model of adjacency graph. The graph construct was based on Voronoi diagram which is further derived from the use of Canny extraction based on curve segments. They designed a graph matching logic for authenticating a person.

Chang, Bowyer, Sarkar and Victor, built a recognition system by taking the help of both face and ear. The technique used by them was PCA.

They manually pass two coordinates of the triangular fossa and the antitragus. There on PCA was used to extracting features point known as ear-space [10].

Yuan and Mu [11], used normalization method based on the concept of an improved Active Shape Model (ASM). Ear normalization was adjusted for any scaling and rotational variation in image. Then Full-space Linear Discriminant Analysis (FSLDA) was applied to perform ear recognition and achieved a recognition rate of 90%. According to **Xie and Mu**, multi-pose problem erupts only when the angle between the subject ear and the camera changes, causing the distortion in an ear image. The distortion in an image degrades the performance of ear recognition. They had provided a solution which give relief from the issue of multi-pose ear, by the use of Locally Linear Embedding (LLE). They further made an improvement on LLE resulting in better algorithm known as ImproveD Locally Linear Embedding (IDLLE). Their algorithm works by making the selection of neighboring data points according to the Euclidean distance. There by enhancing ear recognition performance further high [12].

Zhang and Liu, analyzes the problem of multi view ear recognition. They used B-spline pose manifold construction in a discriminative projection space. This space is formed by the Null Kernel Discriminant Analysis (NKDA) feature extraction scheme. They reported a 97.7% rank-1 recognition rate [13].

Hurley, transformed entire ear image into a force field by pretending that each pixel applies an isotropic force on every pixels which is proportional to pixel intensity and inversely proportional to the square of the distance [14]. Figure 4, represents the force field feature extraction for the human ear.

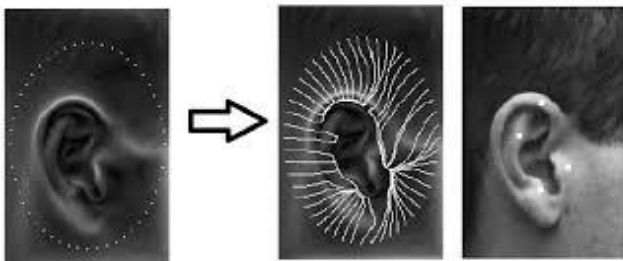


Figure 4. Force Field Feature Extracted from Human Ear

The directional characteristics of force field are used to seek a small number of potential energy wells and channels which are utilized in the matching process. They reported the recognition success rate of 99.2%.

Abdel-Mottaleb and Zhou [15], they also used force field transformation for extracting a feature of an ear. Since the force field converged at the outer edge of an ear to form a ear contours. They achieved the recognition success rate of 87.93%.

Dong and Mu [16], they uses the technique of force field transformation and null-space-based kernel fisher discriminant analysis (NKFDA) for extracting the feature from the human ear image.

Choras [17] gave the geometrical method approach for ear recognition. The contours and centroid is extracted from the subject ear image. Concentric circles is then constructed using centroid. He pointed out two feature vectors stationed in

between the various contours of the ear and the concentric circles. He reported a 100% recognition rate.

Kumar and Wu [18], they utilized the phase facts of Log-Gabor filters for converting into the structure of an ear. The converted phase facts is recorded into a normalized gray level images. Their performance was in between 92% to 95.9%.

Abate et al. [19], they uses GFD (Generic Fourier Descriptor), to raise features from subject ear images. GFD uses the technique of rotation-invariant descriptors. It handle the problems of ear rotation and the change of light illumination. There experimental results shows the recognition rate of 96%.

Sana and Gupta [20], they extracted the structural features of the ear by using Haar wavelet transforms. The Haar wavelet transform was applied to separate the discovered subject image and to calculate coefficient matrices of the wavelet transforms which are clustered in its feature template. The correctness of their algorithm was 96%.

HaiLong and Mu [21], they uses two-dimensional wavelet transform in their algorithms. Features are extracted by assigning an orthogonal centroid algorithm. They announced an average performance rate of 85.7%.

Nosrati et al. [22], they applied a 2D wavelet on an aligned ear image. Template matching algorithm was used for feature extraction. The features was diverged in various positions (horizontal, vertical, and diagonal). They merged these lost images to create a single feature matrix. They achieved a recognition correctness of 90.5%.

Wang et al. [23], they uses both Haar wavelet transforms and Uniform Local Binary Patterns (ULBPs) to recognize subject ear images. After performing the manual segmentation of an image, it is decomposed with a Haar wavelet transform. ULBP were merged in parallel with block-based and multi resolution techniques. At the end, the texture features were classified into identities using the nearest-neighborhood principle.

Yaqubi et al. [24], for extracting feature they used a set of Gabor filters trailed by a maximized operation over multiple scales and positions. Then they used Support Vector Machine (SVM) for ear classification. They obtained a recognition rate of 75%.

Nanni and Lumini [25], used a multi matching assemblage. All matcher was trained by the extracted features from a single sub window of the entire 2D image. The features were raised by convolving on each sub window with a bank of Gabor filters. Afterwards their dimensions were decreased using Laplacian Eigen maps. The best matchers, corresponding to the most discriminative sub windows, were selected by running Sequential Forward Floating Selection (SFFS)

Kumar and Jhang [18], used Log-Gabor wavelets to extract the phase information. All ears is portrayed by a unique ear code or phase template. Hamming distance was then compared between the probe ear images and the database as a classifier. They reported about 90% recognition using 113 subjects.

Dewi and Yahagi [26], they used Scale Invariant Feature Transform (SIFT) to create about 16 key-points for each ear image. They reported a recognition success rate of 78.8%.

Kisku et al. [27], they also used SIFT technique feature descriptors for structural representation of ear images. They developed model for an ear skin color using Gaussian Mixture Model (GMM). Then they used vector quantization to cluster the ear color pattern. Finally, K-L divergence is applied to the GMM framework to register the color pattern. They intimated results enhancement in recognition accuracy by $\sim 3\%$.

V. PROBLEMS IDENTIFICATION

The biggest loophole in ear biometric is that we cannot recognize any individual from the ears. At the same time we can recognize people from their faces. We have several parameters to describe the faces but unfortunately we do not have any standards parameters to describe ears. The success rate in ear identification drops drastically when ear get occluded with subject own hair, head band, ear piece, ear piercing etc [9]. Figure 5, represents a typical example of ear occlusion by hair as well as the ornament worn by the subject. Besides this light illumination and variation of pose are also the prime causes of the problem to be faced by the researcher.



Figure 5. Typical Example of Occlusion

The problem further gets compounded when the image of the subject are not matched by its own probe image. These scenario occurs only due to the variation of the environments, noise and the change in the position of biometric sensor. To overcome these difficulties, tolerance factor is being introduced in the system. These tolerances is defined in terms of False Rejection Ratio (FRR), False Acceptance Ratio (FAR) and Equal Error Rate (EER) or Crossover Error Rate (CER).

VI. SOLUTION FOR EAR BIOMETRIC PROBLEM

Berge and Berger [9] were the first to identify the problem of ear biometric by the means of occluded hair (partial or fully covered by the subject own hair). They suggested the solution when the ear is only suffering from the partial occlusion. According to them, recognition can be done by the use of the thermogram images. These thermogram images are captured by the use of thermal camera. The view of the thermal ear image can be seen in the figure 6. The thermal picture contains the combination of different color. By performing the technique of color image segmentation, one can easily detect and localize ear. But unfortunately no standard algorithm has been developed to resolve the problem using

thermograms.

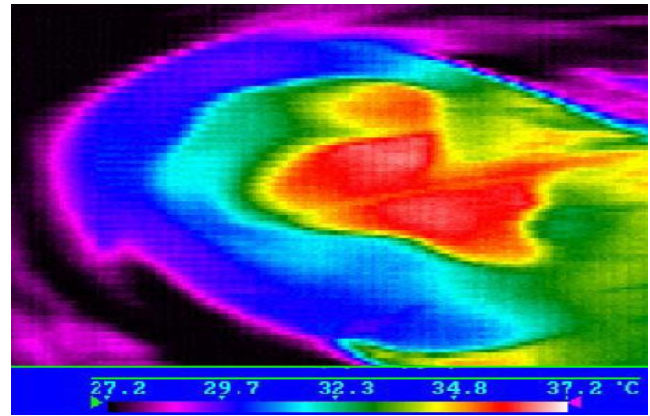


Figure-6. Thermogram of a Human Ear

VII. APPLICATION AREA

Ear biometrics can be applied for the verification and identification or recognition. It is also used for receiving a baby child from day-care or day boarding [28]. Ear biometric can also be merged with the bank credit and debit card, thus enhancing the authentic issues further more. Ear biometric system must be used in the hospital premises to prevent the error of baby swapping, mixing among the new born babies. Ear recognition system is an idle for the task of surveillance and forensic picture examination. It was also reported that German police department uses the benefits of ear biometric to identify the presence of suspects in the surveillance images.

VIII. CONCLUSION

We have presented a detailed report on the ear biometrics. It covers the structural description of human ear. We have explored about the ear database which is freely available to the researcher on the request basis. Besides these, we have also described about the different available method of 2D ear recognition and there recognition success rate. We surveyed about the problem areas and also about how to overcome some of the problem. Ear recognition is still a very young field. Many of the problem issues are yet not been touched, especially the problem related to the occlusion of ear due to hair (partial and complete).

REFERENCES

1. Bertillon A. 'La Photographie Judiciaire: Avec Un Appendice' Sur La Classification Et L'Identification Anthropométriques'. Gauthier-Villars, Paris; 1890
2. Ibrahim MIS, Nixon MS, Mahmoodi S. 'The effect of time on ear biometrics'. In: International Joint Conference on Biometrics (IJCB); 2011. p. 1 6.
3. Kumar A, Wu C. 'Automated human identification using ear imaging'. Pattern Recogn. 2012 March;45(3):956{968. Available from: <http://dx.doi.org/10.1016/j.patcog.2011.06.005>.
4. Prakash S, Gupta P. 'An Efficient Ear Recognition Technique Invariant to Illumination and Pose'. Telecommunication Systems Journal, special issue on Signal Processing Applications in Human Computer Interaction. 2011;30:38-50
5. http://www1.ustb.edu.cn/resb/en/doc/Imagedb\4_intro_en.pdf

6. http://cse.nd.edu/~cvrl/CVRL/Data_Sets.html.
7. Yan P, Bowyer KW. 'Biometric Recognition Using 3D Ear Shape'. Pattern Analysis and Machine Intelligence. 2007 August;29:1297 - 1308.
8. Raposo R, Hoyle E, Peixinho A, Proenca H. 'UBEAR: A dataset of ear images captured on-the-move in uncontrolled conditions'. In: Computational Intelligence in Biometrics and Identity Management (CIBIM), 2011 IEEE Workshop on; 2011.p. 84-90.
9. Burge M, Burger W. 13. In: Jain AK, Bolle R, Pankanti S, editors. 'Ear Biometrics'. Springer US; 1998. p. 273-285..
10. Chang K, Bowyer KW, Sarkar S, Victor B. 'Comparison and Combination of Ear and Face Images in Appearance-Based Biometrics'. IEEE Transactions in Pattern Analysis and Machine Intelligence. 2003 September;25:1160-1165.
11. Yuan L, Mu Z. 'Ear Recognition Based on 2D Images'. In: First IEEE International Conference on Biometrics: Theory, Applications, and Systems (BTAS); 2007. p. 1-5.
12. Xie Z, Mu Z. 'Ear Recognition Using LLE and IDLLE Algorithm'. In: 19th International Conference on Pattern Recognition (ICPR); 2008. p. 1-4.
13. Zhang Z. , Liu H. 2008. Multi-View ear recognition based on b-spline pose manifold construction. In Proceedings of the 7th IEEE World Congress on Intelligent Control and Automation.
14. Hurley DJ, Nixon MS, Carter JN. 'Force Field Energy Functionals for Image Feature Extraction'. Image and Vision Computing. 2002;20(5-6):311 - 317.
15. Abdel-Mottaleb M, Zhou J. 'Human Ear Recognition from Face Prole Images'.In: Zhang D, Jain A, editors. Advances in Biometrics. vol. 3832 of Lecture Notes in Computer Science. Springer Berlin / Heidelberg; 2005. p. 786-792.
16. Dong J, Mu Z. 'Multi-Pose Ear Recognition Based on Force Field Transformation'. In: Second International Symposium on Intelligent Information Technology Application (IITA). vol. 3; 2008. p. 771 -775.
17. Choras M. 'Perspective Methods of Human Identification: Ear Biometrics'. Opto-Electronics Review. 2008;16:85-96.
18. Kumar A., Zhang D. 2007. Ear authentication using log-gabor wavelets. In SPIE Defense and Security Symposium. Vol. 6539
19. Abate AF, Nappi M, Riccio D, Ricciardi S. 'Ear Recognition by means of a RotationInvariant Descriptor'. In: 18th International Conference on Pattern Recognition, ICPR 2006.. vol. 4; 2006. p. 437 -440.
20. SANA, A. AND GUPTA, P. 2007. Ear biometrics: A new approach. In Proceedings of the 6th International Conference on Advances in Pattern Recognition.
21. HAILONG, Z. AND MU, Z. 2009. Combining wavelet transform and orthogonal centroid algorithm for ear recognition. In Proceedings of the 2nd IEEE International Conference on Computer Science and Information Technology.
22. Nosrati M, Faez K, Faradji F. 2007. Using 2D wavelet and principal component analysis for personal identification based on 2D ear structure. In Proceedings of the IEEE International Conference on Intelligent and Advanced Systems.
23. Wang Y, Mu Z, Zeng H. 2008. Block-Based and multi-resolution methods for ear recognition using wavelet transform and uniform local binary patterns. In Proceedings of the 19th IEEE International Conference on Pattern Recognition (ICPR). 1-4.
24. Yaqubi M, Faez K, Motamed S. 'Ear Recognition Using Features Inspired by Visual Cortex and Support Vector Machine Technique'. In: International Conference on Computer and Communication Engineering (ICCCE); 2008. p. 533 -537.
25. Nanni L, Lumini A. 'A Multi-Matcher For Ear Authentication'. Pattern Recognition Letters. 2007 December;28:2219-2226.
26. Dewi K, Yahagi T. 2006. Ear photo recognition using scale invariant keypoints. In Proceedings of the International Computational Intelligence Conference. 253-258. Kisku D. R., Mehrotra H., Gupta P., Sing J. K. 2009a. SIFT-Based ear recognition by fusion of detected key-points from color similarity slice regions. In Proceedings of the IEEE International Conference on Advances in Computational Tools for Engineering Applications (ACTEA). 380-385.
27. Kisku D. R., Mehrotra H., Gupta P., Sing J. K. 2009a. SIFT-Based ear recognition by fusion of detected key-points from color similarity slice regions. In Proceedings of the IEEE International Conference on Advances in Computational Tools for Engineering Applications (ACTEA). 380-385.
28. Ratha N.K., Seniior A, Bolle R.M Automated Biometrics in Proceedings of International Conference on Advances in Pattern Recognition, Rio de Janerio, Brazil, March 2001.

AUTHORS PROFILE

Prof. Devesh Narayan, received B.E. and M.Tech. degree in Computer Sc & Engg. and Computer Technology from Amravaty University and Pt. Ravishankar Shukhla University, India, in 2000 and 2006, respectively., Currently pursuing his PhD. He is currently working as a Associate Prof. in Computer Sc. Dept. at RCET, Bhilai, India.

Dr. Sipi Dubey, appointed as chairperson, Board of studies, CSE, CSVTU, Bhilai(CG) India. Presently working as Prof. in CSE Dept at RCET, Bhilai, India. Her qualification is B.Tech. (Comp. Tech), M.Tech.(Comp.Tech), Ph.D in CSE, from Pt. RSSU, Raipur (CG) India, in year 2010 in image processing, having experience in teaching with 16+ years.