STM JOURNALS

Journal of Artificial Intelligence Research & Advances
ISSN: 2395-6720 (Online)
Volume 6, Issue 1
www.stmjournals.com

Human Identification using Ear as a Biometric: A Review

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Abstract

The science of identifying or recognizing a human or verifying the identity of a person on the basis of behavioral or physiological attributes is called as Biometrics. This paper mainly focuses on studying such biometric systems designed and developed so far using the uniqueness of human ear as a biometric.

Keywords: *Biometrics, ear, recognition, identification*

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INTRODUCTION

There are several human identification or recognition systems available which use the unique physiological attributes of the fingerprint, face, retina, etc. But, the anthropologists have proven the uniqueness of human ear [1, 2, 3] which turns out to be one of the promising attributes that can be used as a biometric for human recognition. In fact, ear as a biometric has several advantages over the others. It is a contact-less biometric as face biometric but face suffers from various expression of the face. Ear biometric may give outstanding performance in recognizing human when side of a face is available. In surveillance videos where the face has occlusion, ear biometric can be used for human identification. Ear is larger as compared to iris, retina or fingerprint which makes it easier to detect.

In this paper, we are trying to present some of the ear detection and recognition systems which also includes different terminologies and methodologies in a compact and clear way.

THE EAR ANATOMY

The ear starts to appear and grows from the pregnancy stage. The external anatomy of the ear is shown in Figure 1.

The structure of the external human ear includes the helix or the outer rim, the anti-helix which is parallel to helix but resides inside, the lobe, and the very distinct U-shaped notch which is known as intertragic notch. The upper shape of the ear also includes triangular fossa and scaphoid fossa. The other parts like cavum, concha, cymba, tragus, anti-tragus are shown in the Figure 1.

THE EAR BIOMETRIC SYSTEM

The typical stages of the ear biometric system are shown in Figure 2.

The typical ear recognition system is actually a pattern recognition system which takes ear images (testing set) as input and then a set of features are extracted from it. The extracted features are then compared with ear images from training set [4]. The typical phases are described as follows.

Ear Detection and Segmentation

In the detection phase the position of the ear being the region of interest is detected using any suitable detection algorithm. According to these positions the ear can be extracted. The detection and segmentation phases are considered as very crucial stages as the accuracy of detection of the ear has very much impact on the recognition output of the ear biometric system.

Ear Enhancement and Normalization

After segmentation, the ear is brought to the phase of enhancement to improve the conformity and normalized in various scales as per need in order to aid in feature extraction.

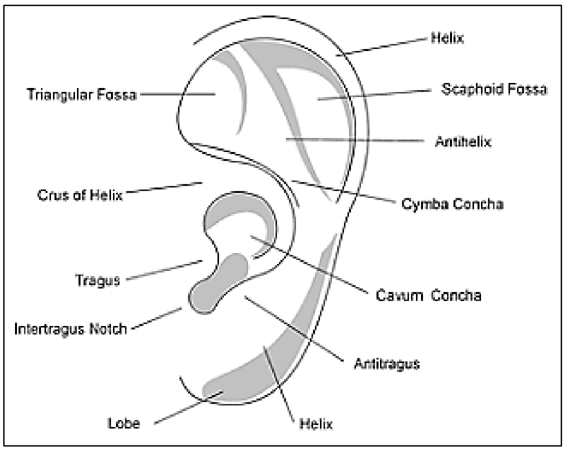

Fig. 1: *The External Ear.*

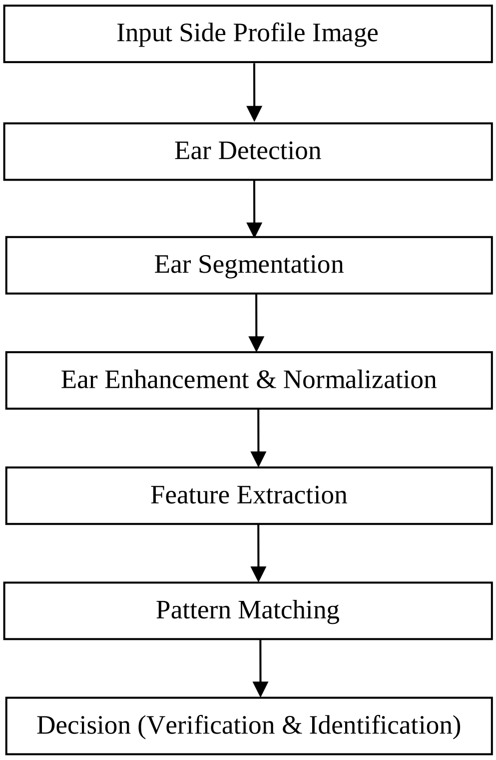

Fig. 2: *Typical Ear Biometric System Phases.*

Feature Extraction

In this phase, the feature vector bestowing various features of the ear is defined and stored.

Pattern Matching

The features extracted from the input image are matched with the features of stored images to identify the input ear.

Decision

The decision of the system is made according the matching score obtained from the matching phase. It verifies the ear image resulting 'Yes' or 'No' in verification mode and returns the best matching ear in case of identification/ recognition mode.

HISTORY OF EAR BIOMETRIC

The potential of the ear to be used as a human identification tool was noticed in the early 1880s by Alphonse Bertillon, who was a French police officer who brought the notion forward of using qualitative and quantitative descriptions of various body parts, including the ear to identify criminals and he termed this as Anthropometry [5]. In 1906, a doctor in Prague named R. Imhofer claimed that only four features were needed to distinguish a set of 500 ears [6]. More than 50 years afterward, some researchers visually assessed 206 sets of ear photographs of newborn babies and inferred that the morphological constancy of the ear could be used to establish a newborn's identity [5]. In 1989, over 10,000 ears were examined by Iannarelli [7] developed an anthropometric technique for ear identification which is considered as one of the prominent works for ear identification. In his work he found that each ear is distinguishable from other ears of the dataset.

FEW WORKS ON EAR BIOMETRICS

Moreno et al. [8] experimented with 2D intensity images using multiple features such as shape, some points of the ear, wrinkles etc. features. Using Neural Network for classification they found a recognition rate of 93% which is best of three different approaches (Borda, Bayesian, and Weighted Bayesian). This technique is further extended by Mu et al. [9] in 2004 by using the structure and shape of the ear as features and artificial neural network was used for the purpose of classification.

Hurley and Carter [10] introduced multiple identification methods combining the results from several neural classifiers using features of the outer ear points, shape and wrinkles, and macro features extracted by compression network. They also introduced three different classification techniques for outer ear or auricle identification.

Chang [11] and Victor [12] used Principal Component Analysis (PCA) method on 2D ear images and compared their results with face biometrics. Due to difference in ear image quality the outcomes of the two systems were different. Chang obtained better results than face biometric whereas Victor's system was found to be worse than the face biometrics results.

Yuizono [13] in 2002 developed a recognition system for 2D ear images using genetic algorithms. In their dataset, they had 660 images collected from 110 individuals and some images from a video stream. The reported rate of recognition was nearly 100%.

Force Field Feature Extraction, a new technique used by Hurley et al. [14] where the image is treated as an array of mutually attracting particles i.e. each pixel exerts a force on all the other pixels. The method had two distinct phases: Image to Force-Field Transformation and Force Field Feature Extraction. They took 252 images where some images were occluded by hair. Using the PCA, they claimed a recognition rate of 99.2%.

Loris Nanni, Alessandra Lumini [15] proposed a method of 2D ear authentication based on fusion of color spaces from which a set of Gabor features are extracted which exploits the powerful properties of color analysis for improvement of performance of the ear matcher. Several 1-nearest neighbor classifiers are constructed to perform matching of different color components. The database used was Notre-Dame EAR dataset.

Arbab-Zavar et al. [16] proposed a new model-based approach for ear biometrics which is a part-wise description of the ear derived by a stochastic clustering on a set of scale invariant features of a training set. The recognition method is a sort of hybrid method incorporating the wavelet based analysis along with parts of the ear recognized by the modal.

Prakash S et al. [17] presented a technique for ear detection in 3D which localizes the ear by using inherent structural details of the ear and is invariant to rotation and scale. The method uses connected components of a graph constructed using the edges of the depth match image of range data. It has two advantages over other existing techniques: this technique does not require any registered 2D image for detection of ear in 3D, and without any additional computational cost it can detect left and right ear simultaneously. Databases used for experiments were Notre-Dame Public database and UND-J2 and found encouraging results in comparison to other 3D ear detection techniques.

Kumar et al. [18] proposed a new approach for a completely automated human identification using 2D images of ear. The segmentation of the ear was also fully automated approach which was based on morphological operators and Fourier descriptors. Complex Gabor filters and localized orientation information were used for extracting the features. The recognition results of the approach achieved average rank-one recognition accuracy of 96.27% and 95.93% on a publicly available database of 125 and 221 subjects respectively.

Chan et al. [19] proposed a new approach for 2D ear identification using quadrature filtering, which has the ability to localize spatial and frequency domain phase information jointly in a segmented image of ear. They developed two new techniques for biometric recognition: the quaternionic quadrature filter and the Quaternionic Code. The datasets used were UND ear dataset and IITD ear database.

Dinkar et al. [20] presents some insights and experimental results by using ear as a non-invasive biometric for human identification. They employed two methods: Weighted Scoring System and Pattern Recognition by Neural Networks. Both left and right ear features were collected from 400 Indians of Goan origin. These features were then converted into numeric scores by a Weighted Scoring System which is further compared for finding uniqueness of ear pattern in same and different persons. The recognition rate of neural networks for some visually similar ear images was found to be 94%.

Islam et al. [21] proposed for a multi-biometric human recognition method using 3D ear and face features. They claimed that this approach was the first of its kind to have feature level fusion extracted from 3D ear and frontal face data. They achieved the identification and verification rates of 99% and 99.4% respectively.

Abaza et al. [22] discussed a problem of human ear recognition in Mid-Wave Infrared (MWIR) spectrum in order to find out the advantages and limitations of Ear Biometrics in day and night environments. They assembled a dual band database consisting of visible and mid-wave IR left and right profile face images and proposed a fully automated thermal imaging based ear recognition system for real-time human identification. They used several feature extraction methods such as Independent Component Analysis (ICA), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA), Scale Invariant Feature Transform (SIFT), Local Binary Patterns (LBP), and Local Ternary Patterns (LTP). Feature extraction by LTP method followed by LBP method yields the best performance (Rank1 = 80.68%) on manually segmented ears and (Rank1 = 68.18%) on ear images that are automatically detected and segmented.

Yahui Liu et al. [23] proposed a unique feature for 3D ear recognition which is ear-parotic face angle of a person. The Ear-parotic face angle is the angle between the normal vector and ear-plane and the normal vector of the face-plane, which is considered as unique and stable features in 3D ear images. The speed and accuracy of 3D ear recognition is enhanced Ear-parotic face angle is able to provide indexing identification as well as hierarchical verification solutions. The search range is reduced to 9.69% from the original which is noticeable reduction in time.

Annpurani K et al. [24] proposed a unique feature of the ear by fusing the tragus feature with the shape of the ear. The tragus is taken as ear feature as it is free from occlusion. A unique enhanced edge detection method to extract the tragus feature of the ear is presented. A line is drawn connecting the maximum coordinate, mid-point and the minimum coordinate. The tragus is found in the mid region of this line. The extracted shape of the ear is then combined with the tragus feature to form the fused template. The authentication rate of the system is calculated by using hamming distance and Euclidean distance method. The experiments were carried out in IITD and AMI databases including occlusion. They also inferred that when tragus is considered as a single feature, tragus gives better results than the shape of the ear as tragus is a unique feature of the ear.

FEW EAR DATABASES

Some of the popular and standard databases for ear biometrics are listed below.

USTB Database

The images in this database are collected by University of Science and Technology, Beijing, is available for science researchers at free of cost. This database has four divisions: Image Database 1, Image Database 2, Image Database 3 and Image Database 4.

Recently in 2016, in corporation with Helloear Co. Ltd., the University has developed a new database named USTB-Helloear, which is photographed under uncontrolled conditions. This database is a large profile database containing more than 610,000 images from 1570 subjects taken from both the left and right sides.

AMI Ear Database

This database was created by Esther Gonzalez during her Ph.D. work consisting of ear images collected from students, teachers and staff. The whole database is spitted into four sub sets of 175 images each. Subset-1 includes subjects from 0-28, Subset-2 includes Subjects from 29-55. Subset-3 includes subjects from 56 to 81 and Subset-4 contains subjects from 82-106. Partially occluded images from some subjects are removed from the database.

UND Database

This database is collected by University of Notre Dame which includes: Collection-E having 942 side view images, Collection-F consisting 464 side profile images, Collection-G consisting 738 profile images and Collection-J2 consisting 1800 profile images.

IITD Ear Database

This database is the collection of images of students and staff at Indian Institute of

Technology, Delhi of age group 14-58 years [25]. Resolution of the images are 272 × 204 pixels and available in jpeg format. In addition to these images the database also provides automatically normalized and cropped ear images. Recently, a larger version of ear database from 212 users with 754 ear images is added to it. This database is good for experiments to be done with images having occlusion and jewelry.

IITK Database

This database is collected by Indian Institute of Technology, Kanpur and available in two subsets. Subset-1 contains 801 side profile images collected from 190 persons and Subset-2 contains images taken from 89 persons, 9 from every individual.

UBEAR Dataset

The fundamental purpose of this database was to remove the constraints of image acquisition scenario so that images can be taken in real world conditions i.e. without any extra care about occlusions and poses and subjects in the moving state etc. which can be useful to evaluate robustness of algorithms.

UCR Database

The University of California Riverside collected this database containing 902 images of 155 subjects, 4 from each [26]. This database is not available for public use.

WVU Database

This database is collected by West Virginia University consisting of 460 video series of 402 subjects and multi series of 54 subjects [27]. Each view starts with left side view and ends with right side view in 2 minutes duration. This database is not open for public access.

CONCLUSION

This paper tries to present the importance of Ear Biometrics as well as its history, some methods and techniques of Ear Biometrics with a focus on some of the recent works related to it and information on some Ear Databases are also included. This paper should help the researchers and scientists who want to work on Ear Biometrics or some related works.

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Cite this Article

Rahul Lahkar, Khurshid Alam Borbora. Human Identification using Ear as a Biometric: A Review. *Journal of Artificial Intelligence Research & Advances*. 2019; 6(1): 99–104p.