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A Review on Recent Advancement in Ear Biometric Authentication System

*Prerna Mehta, #Ela Kumar
*M.Tech Student, #Professor, IGDTUW Delhi India.
*mprerna.30@gmail.com, #ela_kumar@rediffmail.com

Abstract **With advancement in technologies, many biometric systems have been emerged which uses human body parts for biometric system. The ear biometric on the other hand has been given less consideration, compared to other biometrics such as fingerprint or face. The human ear, mostly the outer structure is a new class of relatively invariant biometric feature that has drawn researcher's notice recently because of its distinct structure and higher convenience. This paper discuss work done in ear biometrics for the surveillance and security purpose based on the fact that ear is the least altered body part in terms of physical variations taking place in the body due to surrounding and natural development. The main goal of this paper is to discuss ear biometric advantages over other biometric system. Review of leading work in ear biometric system using 2D and 3D ear images is briefed along with available ear datasets.**

Keywords — Ear, Ear Biometrics, Database and Machine Learning.

I. INTRODUCTION

Biometric systems have been deployed since many years in India and other countries for the reason being, they are more secure, unique to the individuals and does not require to be remembered like the passwords and the Personal Identification Number (PIN). Face and fingerprint are the most widely used biometric systems. In comparison to them, new biometric systems have been developed to overcome their drawbacks. One of them is Ear Biometric.

Ear biometric is basically a system which identifies or verifies an individual based on features of an ear. Ear is known to have a spiral shape. It is build-up of skin, cartilage and six intrinsic muscles. Ear parts are classified under three categories which is inner ear, middle ear and outer ear. For ear biometric system outer ear features are used for classifying an ear for identifying a person. The outer ear is having a scientific name which is known as pinna or auricle as shown in figure 1, which is the only visible part of ear. Ear features which are mainly used in classifying an individual are represented in the following representation of ear.

External auditory canal attaches the middle ear to the outer ear. The Ear drum has a scientific name known as tympanic which is responsible for the hearing of sound in ear. It is of 2-3 cm long in size and is located in middle part of ear. The ear auditory canal is attached to the ear drum which is very sensitive and through the pressure of sound waves it vibrates. The outer edge of the outer ear is known as Helix and the inner edge is known as antihelix. Another part of ear which is known as lobule is a fleshy and soft skin which is at the end of helix. According to scientific study it is highly variable in size and degree of attachment to the face. Concha is surrounded by antihelix, tragus and into which external auditory canal opens. Tragus is a small soft tissue structure which is located on the front margin of the auditory canal.

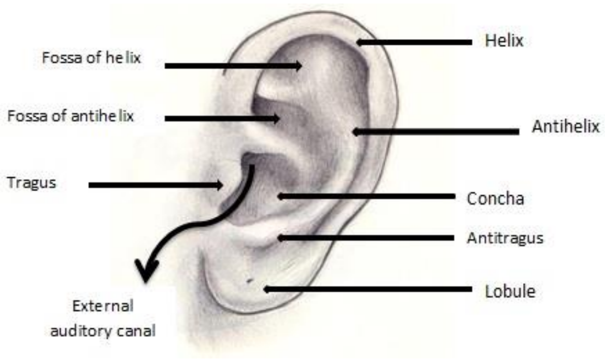

Figure 1: Description of ear unique feature points

Ear biometrics can be used in various applications like in surveillance, IT security, mobile phones [1] and cybercrimes. Different Biometric systems have their own pros and cons, based on that a brief study is made comparing the ear biometric system with other biometric recognition systems below and in table 1:

1. **In comparison with Face Recognition System**

Face recognition system takes face as an input whereas ear recognition system takes ear as an input which is smaller than the face and hence has smaller computational load. Additionally, ear has uniform color while face has non-uniform color distribution. According to the study [2] ear twins also have distinguishable ears and has no change in expression.

2. **In comparison with Fingerprint Recognition System**

Finger recognition system takes fingerprint of a person as an input which needs direct contact of the finger to the fingerprint system whereas ear does not require any touch and contact of ear with the ear recognition system.

Therefore, it reduces chance of harm to the recognition system as well as hygiene problem.

3. In comparison with Voice Recognition System

Voice has many disadvantages over ear biometric system since voice suffers from background noises as well as it changes when a person is ill, as in [3].

4. In comparison with Iris Biometric System

The input of iris requires high resolution cameras whereas ear recognition system can work with normal cameras. Also, it requires additional expensive and harmful rays' hardware. Wearing of glasses also fails the recognition in case of iris recognition system while it works fine in case of ear biometric system.

The rest of the paper is as follows: Section 1 is brief about the work done in ear biometric using 2D image datasets, section 2 contains the literature survey in ear biometrics using 3D datasets., section 4 is brief about the datasets available related to ear biometric and section 5 concludes the paper.

Table 1: Comparison of different biometric identification systems

Biometric systems	Type	Occlusions	Computational Load	Accuracy	Device requirement	Social acceptance
Face	Passive	Scarf, hair, surroundings	High	Medium-low	Camera	High
Fingerprint	Active	Hand Gloves, rings	Low	High	Scanner	High
Iris	Active	Eye glasses	Medium	High	Camera	Low
Ear	Passive	Hair, ear cuffs, surroundings,	Low	Medium	Camera	Low
Voice	Active	NA	High	Medium	Microphone/telephone	Medium
Hand Geometry	Active	Hand gloves, rings	High	Medium-low	Camera	Low
Gait	Passive	Clothes, wheelchair, walking stick, crowd	High	Low	Camera	Low

II. LITERATURE REVIEW ON 2D EAR IMAGES

John D. Bustard et al. [4] proposed ear recognition system from two-dimensional images. To improve the robustness to occlusion they have used SWIFT feature-point model technique. To match features against large gallery images ANN (approximate nearest neighbor) algorithm is used. This technique improved efficiency from occlusion to 30% from above and 18% from side. The major drawbacks of this paper are more computational time in processing is required and it lack of degree of pose variations.

Zhichun Mu et al. [5] proposed a method for ear recognition using local features of ear. Local features are made up of shape feature vector of outer ear & structural recognition rate is the main pitfall of this paper. Andrea F. Abate [1] in year 2019 presents a multi biometric system which records arm gesture & ear during a phone call using mobile sensors for verification of an identity at move. Both physical & behavioural nature has been employed. The total efficiency of the system is increased by using combination of both the biometric systems. The attained EER for multimodal biometric is 0.1. The database is created of 100 subjects which captures multimodal biometric is publicly available.

Convolutional Neural network technique has been proposed by Ibrahim Omara et al. [6] which incorporates three steps. First, deep feature extraction using VGG-M. Second, the deep features obtained from different deep layers are combined using DCA Algorithm & third, pairwise SVM classifier is used for ear recognition. The experiments have been conducted on four datasets IITD I, IITD II, USTB I, USTB II. The average recognition rate on USTB I is 99.33% and on IITD I 99.23.

According to Long Chen [7] applications like access control, passport identification, law enforcement, forensic investigation requires only one image to verify and identify a person. Their work removes the problem of ear recognition using only one sample per person. They have proposed weighted multi key point descriptor & a sparse representation-based classification method that uses only local features of ear image. They have experimented on two databases IITD and USTB III & achieved state of the art recognition performance when there is pose variation & random occlusion in ear images. The main drawback of the work is that time involved is long due to high computational overhead. The average recognition time of one sample is 15.6s on IITD & 10.3s on USTB III.

Alireza et al. [8] proposed ear recognition technique in the presence of illumination. They have used Lenslet Light Field ear database that includes 536 light field images. Combination of HOG & HDG descriptors are used for feature extraction purpose which outperforms all other technique with 88.2% performance.

R.N. Othman et al. [9] proposed an approach for ear recognition when they are partly occluded based on shape context. For ear detection Viola-Jones algorithm has been performed & local shape context descriptor has been used for describing ear images. It is found that the non-occluded ear images give 100% recognition while occluded ones give 57.1% which is the drawback of their work. In paper [10]

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Susan et al., proposed ear detection using faster R-CNN. AlexNet is used as a classifier which is trained with Unified Region Proposal Network (RPN) for ear detection. From experiments it has been seen that the maximum detection rate achieved is 98% when tested on various databases. According to Dogucan et al. [11], from ear images age & gender can be detected. They have used both geometric features & appearance-based features for ear representation. Appearance based features are extracted using deep convolutional neural network like AlexNet, VGG-16, GoogleLeNet, and SqueezeNet which give 94% accuracy in gender classification & 52% accuracy on age classification. Also, they are more superior than geometric features-based methods.

III. Literature Review On 3D Ear Images

Stevard Cadavid et al. [12] rebuilds the 3D ear image using shape from shading from 402 video clips obtained by WVU database. Out of 402 video clips, 60 were used as probe image. There were 42 clips that contained occlusion due to subject wearing earrings, 38 clips due to ear covered by hair & 55 clips due to subject's wearing eyeglasses. The similarity between the reconstructed 3D ear images is done using Iterative closest point algorithm (ICP) & the most stable 3D model is stored in the database which is matched against 60 probe images. The experiments done has rank I 95% recognition rate & 3.3 % error rate. The drawback of the SFS algorithm used is that it suffers from illumination variation conditions.

In paper [13], Jindan zhou et al. proposed a fully automatic 3-D recognition system which uses two techniques for feature extraction. They are the first one to propose such recognition system which uses local as well as holistic features as a combination for recognising ears. They used histogram of index shape (HIS) and surface patch histogram of index shape (SPHIS) for representing feature points and encoding shape of ear. For efficient matching of ears, surface voxelization is used instead of root mean square distance (RMSD). It is efficient than RMSD since it reduces the root mean square error (RMSE). This approach yielded rank-1 recognition rate of 98.3% and equal error rate (EER) of 1.7%. The main drawback is local feature matching speed is less. Ping Yan [14] presented a fully automatic ear biometric system which can deal with presence of earrings and with a limited amount of occlusion by hair using 3D information. An active contour approach is used for segmenting ear and ICP approach for matching ears. It has rank-1 recognition rate of 97.8% and achieves EER of 1.2%.

I.I Ganapathi et al. [15] introduced a method for ear recognition that recognizes feature key points of the curvilinear structure of the co-registered 2D ear and plotted them to their corresponding 3D ear images. Feature descriptor is used which is composed of the neighbourhood points around each mapped key points in 3D. The alignment of 3D probe & 3D gallery is made using the key feature points with the help of ICP (Iterative closest point) technique & afterwards matching is done. The experiments conducted for identification & verification of a person included noise & occlusions. The results of the proposed technique are 98.69% which is conducted on UND collection J2 dataset. In his other work [16], he has proposed a global 3D descriptor & for higher ranking recognition performance he has combined local & global descriptors. The experiments conducted on two databases UND collection 2 & our in-house showed that the combined four popular local 3D descriptors & proposed descriptor yields rank I recognition rate of 98.69% on UND collection 2 & 98.9% on our in-house database.

According to Lin Zhang [17], they are first to modify LC-KSVD, a state-of-the art model for supervised dictionary learning. They have proposed LCKSVD_LHST method for 3D ear classification for identification of a person. For feature extraction they have used local histograms of STs (LHST). Experiments were conducted on the largest 3D ear scan dataset UND Collection J2. Four subsets were created which has 92.86%, 95.88%, 98.63% & 100% accuracy making their method achieving better recognition accuracy than other state-of-the art methods. Fully automated 3D ear segmentation is performed in Sayan Maity et al. [18] work. They have performed segmentation of 3D ear using active contour algorithm. Afterwards, categorization of 3D ear is carried out using K-dimensional (KD) tree (balanced split) with indexing & pyramid tree (unbalanced split) without indexing. Experiments show that pyramid tree has better recognition accuracy 96.87% on 10% reduction space & computation time as compared to KD tree. Rank I recognition of 98.5% is computed on UND Collection J2 without Indexing.

IV. Summary Of Publicly Available Ear Databases

Data acquisition plays an important role in supervise machine learning system. Various images are registered in a database for identification and verification purpose in research and biometric system. There are two types of images which are stored in a database. The database also plays an important role in benchmarking a system. These are probe images (test images) and gallery images (training set images). The least difference between them identifies a person. Various ear databases already available are discussed below.

1. IIT Delhi

Indian Institute of Technology Delhi database is available to the public for free since 2011. The collection has been started since October 2006 by various volunteer students and staff at IIT Delhi, New Delhi, India. Images are obtained in indoor environment from distance using an imaging setup. The age group lies between 14-58 years. 3 images of 121 subjects have been enrolled in the database. Database has raw images and pre-processed images. Raw images are in jpeg format of 272 x 204-pixel resolution and pre-processed of 50 x 180 pixels. In India it has the highest number of downloads. The dimensionality of images is in 2D.

2. UND

University of Notre Dam has two collections, collection E and collection F. The dimensionality of images is in both 2D and 3D. 150 total numbers of subjects are registered in this database and have total 1800 images. The dataset is licensed.

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3. AWE

Annotated web ear dataset has 1000 images registered of 100 subjects is available since year 2016. AWE has their own AWE toolbox which is written in MATLAB and has already dataset included in it. The dataset has partial occlusions and has 2D dimensionality.

4. UBEAR

The dataset images are captured under uncontrolled conditions and are available since 2011. It has 4430 total images of 126 subjects of age group varying from 0-99 years. The format of images is in tiff and has 2D dimensionality of 1280 x 960-pixel resolution.

5. AMI

Mathematical analysis of images ear database is available to the public for free for the use in scientific applications. It is created by Esther Gonzalez during her work on the PhD in computer science. It contains images of students, staff and teachers of computer science department in indoor environment. The age group lies between 19-65 years and has total 175 images of 100 subjects. It has both 2D and 3D dimensionality and has partial occlusions. Nikon D100 camera is used to capture these images under same lighting conditions. The whole database has total 4 subsets.

6. USTB I

In year 2002, total 60 volunteers' right ear were photographed with digital camera. Every volunteer 3 images were taken under different lighting conditions. Total 185 images were registered. The format of image is in bmp and has no occlusions. The dimensionality if image is in 3D having 300 x 400 pixels.

7. USTB II

In year 2003-2004, total 77 subjects' 308 images using CCD Camera were registered. 2-meter distance is maintained between camera and subject. Each image is 24-bit color image of 300 x 400 pixels. The second and third datasets have same illumination condition will capturing with the first one; but are separately rotated by +30 degree and -30 degree with respect to the first one.

8. USTB III

In year 2004, total 144 images of 24 subjects were registered having partial occlusion and 3D dimensionality of 768 x 576-pixel resolution.

9. UCR

University of California riverside ear database, in year 2007 made ear dataset which has total 902 images of total 155 subjects. The ear dataset is private and is only available on demand. It has partial occluded ear images with hair and earrings. The age group lies between 20-35 years and has both 2D and 3D ear images of 200 x 200 pixels.

Table 2: Summary of different ear databases

Database & Year	Subjects	No. of Images	Age Group (In Years)	URL	Occlusions	Format	Accessories	Dimensionality	Gender	Image Resolution (In Pixels)
IITD [14] (2011)	121	754	14-58	[19]	none	Jpeg	Yes	2D	Both	Raw: 272 x 204 Pre-processed: 50 x 180
UND (2003-2005)	150	1800	NA	[20]	NA	NA	NA	Both 2D & 3D	Both	NA
AWE (2016)	100	1000	NA	[21]	Partial	NA	Yes	2D	Both	NA
XM2VTS (2014)	295	1180	NA	private	Partial	Ppm	Yes	Both 2D & 3D	Both	720 x 576
UBEAR (2011)	126	4430 15 fps	0-99	[22]	Partial	Tiff	Yes	2D	Both	1280x 960
AMI	100	175	19-65	[23]	Partial	Jpeg	None	Both 2D & 3D	Both	492 x 702
USTB I (2002)	60	185	NA	[24]	None	Bmp	None	3D	Both	300 x 400
USTB II (2003-2004)	77	308	NA	[25]	None	Bmp	None	3D	Both	300 x 400
USTB III (2004)	24	144	NA	[26]	Partial	Bmp	None	3D	Both	300 x 400
UCR (2007)	155	902	20-35	[27]	Partial	NA	Yes	Both 2D & 3D	Both	200 x 200

V. CONCLUSION

The essential objective of this survey paper is to give an overview of the fast growing and exciting areas of automation in biometrics using Ear as feature. Basis on the study of ear biometric system, it is concluded that the features of ear are unique in terms of physiological and behavioral variation. The shape and color of ear are consistent. The challenges include presence of occlusion such as accessories, hair and lightening irregularity, which make the processing difficult. Also, it has been evaluated that 3D ear recognition is intricate than the 2D ear recognition due to much complex feature extraction & 3D

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representation of ear. It has been seen that most of the 3D ear recognition system uses UND & USTB ear databases whereas IITD, AWE, AMI ear database is used for 2D ear recognition.

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