Ear Biometrics: A Survey on Ear Image Databases and Techniques for Ear Detection and Recognition

Tejas. V. Kandgaonkar[1] , Rajivkumar. S. Mente[2], Ashok. R. Shinde[3] and Shriram. D. Raut[4]

[1,2,3,4] *Department of Computer Science, Solapur University, Solapur*

ABSTRACT

Identifying the people by using their ear is the emerging trend in the modern era. Biometrics deals with the procedure to identify people, by using their measurable, unique and permanent features such as fingerprint, iris, face, vein, DNA, hand writing, hand geometry and many more. Biometrics serves as integrated part of modern security systems. This paper discuss about the ear biometrics. Human ear is the unique and clearly visible trait that is permanent for his/her lifetime. The increasing age of human being affects very less on the ear. This paper provides a detailed survey of 16 most popular image databases available for ear biometrics, which will be helpful for the researchers on which they can perform the experiments. This paper includes a comparative study of techniques used for ear detection and ear recognition techniques. Current research work in ear biometrics is limited to database of images captured under certain conditions.

Key words: Authentication, Biometrics, Ear Recognition, Ear detection, Ear Image Databases, Side profile images.

Introduction

Now a days there is emerging need to automatically authenticate the human. Due to this biometrics has become the active research field of modern era. Traditional recognition systems such as cards with identity number and password can be forgotten, stolen or lost. On the other hand biometric features are measurable, unique and permanent for individual. Biometrics is the automated procedure to recognize a human being by using physical features or behavioral features such as face, iris, fingerprints, palm and voice (Raut, 2014). Nowadays biometrics plays an important role in order to authenticate user in security systems as well as to identify the person. It is one of the external features, that is clearly visible and we can identify the person from his/her side profile (Jain, 2004).

Figure 1: Side profile of user

This paper includes the survey of the current research work done in the area of ear biometrics. Objective behind this survey paper is to help researchers and make them aware about ear as significant biometric trait by

a) Reviewing more research paper's contents and determine the techniques used for ear biometric systems.
b) Listing multiple standard image databases available for ear recognition systems.
c) Listing the crisis in ear biometrics.

This paper has multiple sections as: Section 2 gives the working model of ear biometric systems and phases involved in it; Section 3 describes the major milestones in history of ear recognition; Section 4 presents commonly used image databases of ears available for research; Section 5 gives literature review of various ear detection methodologies available; different techniques used to recognize the ear are given in Section 6 and lastly in Section 7 focuses on the predicaments in ear biometrics.

Ear Biometric System

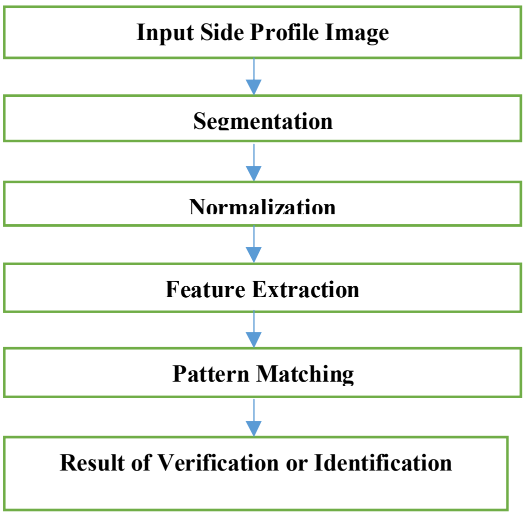

Figure 2: Ear Biometric Model

An ear biometric is nothing but pattern recognition system. It will accept test images of ear from the user. Then set of features will be extracted from it. These features will be compared with the train images. Ear biometric system works in two manners, either for verification or identification.

The phases in ear recognition system include:

1. Segmentation

   The initial task is to locate the position of ear in the image which serves as our area of interest. According to these positions the ear can be extracted.

2. Normalization

   The segmented ear is then exposed to enhancement operations to improve fidelity of image in order to aid in feature extraction and matching the pattern.

3. Feature Extraction

   After the normalization next task is to define a feature vector that includes various features of ear.

4. Pattern Matching

   Then extracted features from input image will be matched with that of the features from stored images in the database to identify the input ear.

5. Result

   According the result of comparison in matching phase the decision will be made. If ear biometric system is in verification mode then either ‘yes’ or ‘no’ will be the final output. While in identification mode best matching record will be returned.

History of the Ear Recognition

The probability of recognizing the humans by using the shape of their outer ear was first recognized by Alphonse Bertillon in1896 (Bertillon, 1896)Bertillon made some measurements for Bertillonage System to identify the criminals.

The detail structure of human ear is unique in the universe but it also remains unchanged for the lifetime of human being. This external feature is clearly and easily visible. The anatomy of ear is given in figure 3 (a) as 1–Helix Rim, 2-Louble, 3-Antihrlix, 4-Concha, 5-Tragus, and 6-Antitragus, 7-Crus of Helix, 8-Triangular Fossa and 9-Incisure Intertragica.

The first ear recognition system was developed by American police officer Iannarelli in 1949 (Iannarelli, 1989).In his system 12 measurements were taken from an ear image manually. Upright, flat, anti-diagonal and diagonal lines were drawn from that center point to interconnect internal and external curves as shown in figure 3 (b).

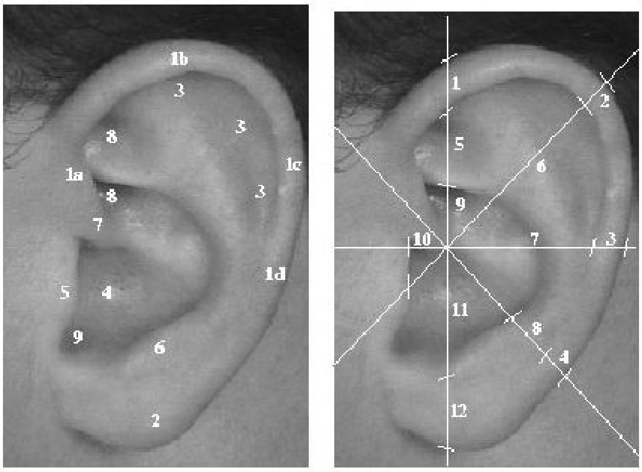

Figure 3: (a) Ear Anatomy (b) Measurements

First fully automated ear recognition system was developed by Moreno et al.[1999] based on multiple features such as shape, wrinkles, ear points, features by compression network and then combined the results using artificial neural network as classifier.

In 2004 Later, Mu et al. extended this technique by using ear structure and shape of ear as feature vector set and used artificial neural network for the classification purpose.

(Yuizono, 2002) viewed this problem of ear recognition as search optimization problem and used genetic algorithm to reduce the error which demonstrated 99-100 % of accuracy.

Databases

Most popular standard image databases available for ear recognition system or ear biometrics are described in brief below,

1. *WVU (West Virginia University) Database*

This ear database was composed with the help of a system, which consists of PC, Camera, and Linear Actuator, Light and structural framework (Fahmy, 2006). This database consists of 460 video series of 402 subjects and multi series of 54 subjects(Abaza, 2008). Each video starts with left side view while ends with the right one, within two minutes. This database is private.

2. *USTB (University of Science and Technology, Beijing) Databases*

The ear database collected by University of Science and Technology, Beijing is available for researchers at free of cost(USTB, 2014).

Image Database 1: This database consists of total 180 images of right ear of 60 subjects. There are 3 images of each subject i.e. they are normal image of ear, image of ear with trivial angle rotation and image under different lightening condition.

Image Database 2: This database includes total 308 ear images of 77 subjects. They are side view image (0^0), 2 images with difference in angle ($+30^0$ & -30^0) and one includes lighting dissimilarity.

Image Database 3: This database consists of the ear and face images of 79 subjects. For each subject, two images are taken at the angle of 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 60 degrees. It includes ear images with partial occlusion, trivial occlusion and normal occlusion.

Image Database 4: CD cameras placed round the person at every 15 degrees and images of ear and face were captured. This database contains images of 500 subjects.

3. *UCR (University of California Riverside) Database*

This ear image database is collected by University of California Riverside. This database contains 902 images for 155 subjects with 4 images each (Chen, Human ear recognition in 3D., 2007). 12 subjects have partially occluded ears. 17 subjects are female. 6 subjects have earrings. This database is private.

4. *UND (University of Notre Dame) Databases*

This database collection by University of Notre Dame is public use with no any charge [UND 2014]. It includes following collections:

Collection F: This collection consists of total 464 side profile images of 114 subjects captured in visible light.

Collection E: This collection includes 942 side view images of 302 people in 3D and corresponding 2D.

Collection G: This collection has 738 profile images of 235 subjects in 3D and corresponding 2D.

Collection J2: This is the collection with 1800 profile images of 415 subjects in 3D and corresponding 2D.

5. *UMIST Database / Sheffield's Database*

This database was collected by the University of Sheffield, UK. It was previously known as UMIST. This database includes 564 images of 20 people while circling their head from side view to front. This small database is freely available for public use (UMIST, 2014).

6. *XM2VTS Database*

The XM2VTS (Extended Multi Modal Verification for Teleservices and Security applications) database consists four recordings of 295 subjects, recorded in four sessions each at duration of 4 months(XM2VTS, 2014). Each soundtrack has a six speech shots with 2 rotary head shots. XM2VTSDB includes high class colored images, 32 KHz 16-bit audio files, video series with a 3D Model.

7. *FERET Database*

FERET (Facial Recognition Technology) database consists of 14126 images with1199 unique and 365 identical images (Phillips, 1998). For some subjects, there are images of left profile and right one. These images are mostly appropriate for 2D ear recognition. This database is public use but not free of cost.

8. *CAS-PEAL Database*

This database has 99,594 images of 1040 persons (595 men and 445 women) with different Posture, Appearance, and Lighting(Gao, 2004). For each person, 9 cameras were placed in a horizontal semicircular shelf at equal spacing. They have considered 5 types of expressions, 3 types of glasses, 3 types of caps, and 15 lighting directions. This database is partially available for public use.

9. *WPUT Database*

The West Pomeranian University of Technology has collected this database [Frejlichowski et al. 2010]. The database contains 2071 images of 501 subjects. For each subject, 4 to 8 images are there, which were taken at different illuminations. The people are also wearing headdress, jewelries, hearing utilities and some ears are occluded by hair. This database is freely available to download.

10. *Database by IIT Delhi*

The IIT Delhi Database is contributed by the Hong Kong Polytechnic University (Kumar A. a., 2012). It has ear images that were composed at the IIT, New Delhi. The database contains 421 images of 121 subjects. This database is freely available for researchers.

11. *Database by IIT Kanpur*

The IITK database was provided by the Indian Institute of Technology in Kanpur [Prakash and Gupta 2011]. This database consists of two subsets.

Subset I: It comprises of 801 side view images of 190 people, 2 to 10 images per person.

Subset II: This set includes images of 89 subjects. 9 images for every person were taken at 3 dissimilar postures. Each pose was captured at three different scales.

12. *SCFace*

This database is composed by the Technical University of Zagreb (Grgic, 2011). This database has 4160 images of 130 people. Unfortunately, the ears are not visible on these images as images were taken at front angle. However the database also contains the subject images at different poses. These poses include the right and left profile. This database is publicly available for researcher for free.

13. *YSU*

The Youngstown State University composed this database of the 259 subjects, 10 images for each subject (Al Nizami Ha, 2009). The images are captured from a video sequence which includes the images of subject in poses between 0^0 and 90^0. It also has sketches from 50 randomly nominated people from a front angle. This database is freely available for researchers.

14. *NCKU*

This database is collected by National Cheng University of Taiwan (NCKUDB). It comprises of 37 images for every person of the 90 people. It is freely available on university website to download. Each image is captured from left profile to right profile of the subject in 5 degree steps in same lighting conditions by maintaining same distance between camera and object. Some ear images are partially or fully occluded by hairs. This database is freely available to use.

15. *UBEAR*

This database contains 4430 images of 126 subjects (Raposo, 2011). These ear images were captured in uncontrolled environments and under unrestrained protocols. This includes images of subjects with headdresses, jewelry and ears occluded by hairs. It includes images of subjects at diverse postures such as viewing towards camera, looking up or down. These images are extracted from video sequence. This database is freely available for public use.

Summarized information about all these ear image databases is given in table 1.

Table 1: Ear Image Databases

Database	Total	Subjects	Cost	Specification of images/ video sequence
WVU	460 Videos	402	----	Video starts with left profile while ends with the right one, within two minutes.
USTB			Free	
Dataset 1	180 Images	60		Ordinary ear image, Image with trivial angle, image under diverse illumination.
Dataset 2	308 Images	77		Profile image, Images with $+30^0$ and -30^0, Image under different illumination.
Dataset 3	1738 Images	79		2 images per angle - 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 60 degrees.
Dataset 4	8500 Images	500		17 cameras around the subject at each 15 degrees and images were taken.
UCR	902 Images	155	----	12 subjects with partially occluded ears. 17 subjects are female. 6 with earrings.
UND			Free	
Collection F	464 Images	114		Side profile images.
Collection E	942 Images	302		3D and equivalent 2D images.
Collection G	738 Images	235		3D and equivalent 2D images.
Collection J2	1800 Images	415		3D and equivalent 2D images.
UMIST	564 Images	20	Free	Subjects circling their head from left side to front view.
XM2VTS	4 Recordings	295	Cost	High class color images, 32 KHz 16-bit audio files, video series
FERET	14126	1199	Cost	365 Duplicate set of images.
CAS-PEAL	99594	1040	Free	Considered 5 types of expressions, 3 categories of glasses, 3 classes of caps, and 15 lighting directions.
WPUT	2071	501	Free	Images under different lightening conditions.
IIT Delhi	421	121	Free	3 images per subject in indoor environment.
IIT Kanpur			Free	
Subset I	801	190		2-10 images per subject.
Subset II	801	89		9 images per subject at 3 poses.
SCFace	4160	130	Free	Includes left and right profile images.
YSU	2590	259	Free	Images of subject with poses between 0^0 and $90^{0.}$
NCKU	3330	90	Free	37 images per subject. Includes images of subjects with ears occluded partially or fully.
UBEAR	4430	126	Free	Images of subjects at diverse postures such as watching to camera, watching up or down.

Source: Primary Data

Ear Detection Techniques

Locating the exact position of image by using segmentation techniques is the essential step in order to detect ear for further biometric process. Some of the techniques are described in this section.

1. *Semi-Automated Ear Recognition*

These techniques involve user interaction and then further computerized processing. User has to specify the points on image at the position of ear. According to these points the image will be segmented further.

(Yan P. B., 2005) used a technique that requires user to specify the line between face and ear, and another line from top of ear to bottom. Based on these two lines the segmentation is to be performed.

(Alvarez, 2005)used snake algorithm which requires user to draw an ear outline. Based on this outline the segmentation of ear performed.

2. *Template Matching Technique*

Chen and Bhanu [2004] performed their experiment on images from UCR database of 30 subjects. They used average histogram of shape index as template. By using the methodology consisting of the steps as edge discovery and thresholding, dilation of image, cataloging and master matching, they have achieved 91.5 % of accuracy.

Later on (Chen, Shape model-based 3D ear detection from side face range images, 2005) signified shape model of ear as discrete 3D vertices with respect to the helix and anti-helix of ear. They formed clusters by grouping these different edge sections. They register ear shape model with the edges. They have detected the ear in the area with less mean registering error. They performed this experiment on UCR database images of 52 subjects and achieved 92.6% accuracy.

(Ansari, 2007) performed the experiment on the basis of helix curves of ear that moves parallel with each other. By using the canny edge detector they extracted the edges. They further classified these edges as concave edges and convex edges and from this they determined the helix edges. They collected database of 700 images of left and right ear, after performing the above experiment on it, they achieved 93% accuracy.

3.*Morphological Operations*

(Hajsaid, 2008)used low cost features for division and Bayesian classifier for classification of these segmented images. They performed this experiment on WVU database of 3750 images of 376 subjects and achieved 90% accuracy.

4. *Shape as Feature*

(Arbabzavar, 2008) achieved 100% detection rate on 252 images from XM2VTS database, of 63 subjects and achieved 91% detection rate on collection F dataset of UND database. They used elliptical shape of ear as feature to detect ear using a Hough Transform (HT).

(Zhou, 2010)used HCS (Histograms of Categorized Shapes) as feature set in order to detect ear in 3D. They used approach of sliding window and SVM (Support Vector Machine) classifier. They achieved 100% detection rate on dataset of 142 images from UND collection F database.

5. *Viola-Jones Method*

For ear detection (Islam, 2008) used nested Adaboost classifier based on Haar feature. In face recognition domain this technique is identified as Viola-Jones method(Viola and Jones 2004). They used Adaboost classifier to identify the ear from images with hair occlusion and poor quality of image. They achieved 100% detection rate on UND database of 203 profile images and 54% on XM2VTS database images with 54 ears out of 104 were partly blocked by hairs.

The same technique of Adaboost was used by (Yuan L. and Zhang, 2009). They achieved much better results on the images with multiple subjects in same image too. They achieved FRR 3 and FAR 3.6 on 166 images from CAS-PEAL database. On 220 images of USTB database they reported FRR 0.5 and FAR 2.3. They achieved FRR 2.1 on 48 images of UMIST database.

6. *Hybrid Techniques*

Skin Color and Template-based Technique: (Prakash S. J., 2009)used skin color and pattern matching technique to detect the ear automatically from the side view image of subject. They classified the image as skin region and non-skin region. They used to perform search for ear in skin region only. Then to validate the ear they used template matching technique using shape descriptor. They achieved 94% accuracy by applying the above technique on 150 side profile color images of different subjects.

2D Skin color and 3D Pattern matching: (Chen, Human ear recognition in 3D., 2007) used skin color from color images and edges from various template images for ear discovery. They clustered resulting segments of edges of helix and antihelix parts of ear. They achieved 99.3 % accuracy on UCR database and 87.71 % accuracy on UND database.

Shape of low level features: Based on the technique of analogy of light rays (Cummings, 2010) achieved 99.6% accuracy on XM2VTS database. This ray transformation highlights the spiral shape of ear and sight frames. They used oval shape of helix to segment the image. They achieved 99.6% accuracy using XM2VTS database.

Ear Recognition Systems

1. *Geometry of curves of Ear in 2D*

Choras extracted ear curves and formed centroid. Then by using that centroid from the ear images he formed concentric circles (Choras M. , 2004). Based on points between concentric circles and ear contours, they used two feature vectors. He achieved 100% accuracy by performing experiment on the database of 240 images of 12 subjects.

By using representation of ear contours and geometrical parameters method, Choras and (Choras M. a., 2006)extra 2 more geometric feature vectors. Then they performed comparative study by using various methods on the collected database of 102 ear images. Different methods reported FRR between 0 to 9.6%.

2. *Fourier Transformation*

(Abate, 2006) used Generic Fourier Descriptor (GFD) to excerpt ear features. This is the rotation invariant descriptor. They collected the ear image database with two datasets. First dataset includes 210 ear images of 70 subjects. They captured 3 images for each subject, one at 0^0 (looking ahead), at 15^0(looking up) and at 30^0(looking up) rotation. Second dataset consists of 72 ear images of 36 people. It includes 2 images per person, viewing up with free revolution angle. They achieved 96%, 88% and 88% results for images with 0^0, 15^0 and 30^0 rotation respectively.

3. *Wavelet Transformation*

(Sana, 2007)used Haar wavelet transform for extraction of the texture of ear from the image. They have used pattern equivalent technique for ear detection. Then they applied Haar wavelet transform to decompose detected ear from the image and to calculate coefficient matrices of wavelet transform. Later they grouped this matrix to template. By using Humming distance they calculated the matching score. They achieved 96% accuracy on images of 600 subjects from IITK database and images of 350 subjects from Saugor database. To recognize ear, (Wang, 2008) used Haar wavelet transform and Uniform Local Binary patterns (ULBPs).They segmented ear image manually and later decomposed it by Haar wavelet transform. Then combined ULBPs with block-based and multi-resolution methods for texture feature extraction. Finally they applied nearest neighbor classifier for the classification purpose. They achieved 100%, 92.4%, 62.66 % and 42.41% recognition rate for 5^0, 20^0, 35^0 and 45^0 pose angles respectively.

(Hailong, 2009) used less frequency images derived by applying 2D wavelet transform. Later they applied orthogonal centroid algorithm and extracted features. They achieved 85.7% performance rate on USTB dataset II (77 subjects) and 97.2 % on USTB dataset IV (79 people).

4. *Gabor Filters*

To extract ear codes from one dimensional gray-level signals, (Kumar A. a., 2007) used Log-Gabor wavelets. They used unique code or phase template for each ear. For the classification they used Hamming distance for comparison of input image and the database. On UND collection E database of 113 subjects, they achieved 90% recognition rate.

(Watabe, 2008) used the technique of flexible graph matching and PCA (Principal Component Analysis). They used vertices categorized by the Gabor jets antihelix, posterior crus of antihelix and anterior crus of antihelix. They represented the ear as a graph using these vertices. They developed 'jet space similarity' algorithm for ear discovery. They performed this experiment on 362 images (2 images for each person) of the XM2VTS database. They achieved 0.1% FAR and 4% FRR.

5. *SIFT*

(Kisku, 2009) used scale invariant feature transform for illustration of ear. They used Gaussian Mixture Model to develop ear skin model and vector quantization for clustering of ear color pattern. Then they used K-L divergence to it. By manual segmentation they mined SIFT main points. They performed this experiment on 800 images (2 images for each subject) and achieved 96.93 accuracy.

6. *3D Ear*

(Yan P. B., 2005)represented 3D ear recognition using Iterative Closest Point (ICP) algorithm. They used UND collection F database. They used two-line landmark for segmentation and achieved 98.8 recognition rates.

(Islam, 2008) used the ICP for implementation of completely automatic 3D ear recognition system. They used 2D Haar feature for detection of ear and then cropped corresponding 3D segment. They achieved 93% recognition rate on UND collection F database images.

Crisis in Ear Biometrics

1. *Automatic Detection of Ear*

In many ear biometric systems, they used previously segmented ear images as database. Automatic discovery of ear from real-time images is still one of the mysterious crisis. Only few databases are available that are collected in uncontrolled environments. If ear recognition system implemented on such databases then it will be more realistic and reliable system.

2. *Ear Symmetry*

The symmetry of left ear and right ear of same person is not fully understood yet. There are only few literature that deals with Ear symmetry such as (Yan P. a., 2005), (Xiaoxun, 2007). But they used ear symmetry for enhancing their results obtained by single ear images. Iannarelli's experiment also described that the outer ear characteristics can be inherited.

3. *Occlusion*

Rather than illumination variations and variation in pose of subjects the major problem in front of the researchers is the collusion of ear .The ear can be partly or completely occluded by hairs or any other stuff such as headphones, jewelry, goggles, caps, headdresses or hearing aids.

Summary and Conclusion

This review is the presentation of survey of ear biometrics. For any scientist who wants to work on ear biometrics, this paper will give them the information about the databases available for their work. This paper will also provide some important factors regarding to these databases such as availability, cost, number of images, technique used for acquisition of images. This review focuses on the various ear detection techniques used by researchers yet, such as semi-automated technique, template matching, morphological operations, shape feature, Haar feature and some hybrid techniques and the result they achieved by sing these techniques too. This will helpful for the researchers to detect ear from the image and perform further operations on it. This paper also highlights some ear recognition techniques such as 2D ear curve geometry, 3D features, wavelet transform, Fourier transform, Gabor filter and SIFT. This paper will be helpful to acme ear biometrics as extensive part of face recognition to contribute multimodal biometrics.

References

NIST mugshot identification database (MID) (2014). Retrieved from http: //www.nist.gov/srd/nistsd18.cfm.

Abate, A. N. (2006). Ear recognition by means of a rotation invariant descriptor. *18th IEEE International Conference on Pattern Recognition (ICPR)*, (pp. 437–440).

Abaza, A. (2008). *High performance image processing techniques in automated identification systems. Ph.D. thesis,* West Virginia University, Morgantown-WV.

Al Nizami Ha, A.-H. J. (2009). A biometric database with rotating head videos and hand drawn face sketches. *3rd IEEE international conference on Biometrics: Theory, applications and systems, Piscataway, NJ,USA* (pp. 38-43) IEEE Press. .

Alvarez, L. G. (2005). Fitting ear contour using an ovoid model. *IEEE International Carnahan Conference on Security Technology*, (pp. 145–148).

Ansari, S. a. (2007). Localization of ear using outer helix curve of the ear. *IEEE International Conference on Computing: Theory and Applications*, (pp. 688–692).

Arbabzavar, B. a. (2008). Robust log-gabor filter for ear biometrics. *18th IEEE International Conference on Pattern Recognition (ICPR).*

Bertillon, A. (1896). *Signaletic Instructions Including: The Theory and Practice of Anthropometrical Identification. R.W. McClaughry translation,* The Werner Company.

Chen, H. a. (2004). Human ear detection from side face range images. *IEEE International Conference on Pattern Recognition (ICPR)*, (pp. 574–577).

Chen, H. a. (2007). Human ear recognition in 3D. *IEEE Trans. Pattern Anal. Mach. Intell. 29, 4,* , 718–737.

Chen, H. a. (2005). Shape model-based 3D ear detection from side face range images. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (pp. 122–127).

Choras, M. (2004). Human ear identification based on image analysis. *7th IEEE International Conference on Artificial Intelligence and Soft Computing (ICAISC).*

Choras, M. a. (2006). Geometrical algorithms of ear contour shape representation and feature extraction. *6th IEEE International Conference on Intelligent Systems Design and Applications (ISDA).*

Cummings, A. N. (2010). A novel ray analogy for enrollment of ear biometrics. *IEEE Conference on Biometrics: Theory, Applications, and Systems (BTAS).*

Fahmy, G. E. (2006). The effect of lighting direction/ condition on the performance of face recognition algorithms. *SPIE Conference on Human Identification.*

Frejlichowski, D. a. (2010). The West Pomeranian University of Technology Ear Database: A Tool for Testing Biometric Algorithms. *Image Analysis and Recognition. vol. 6112 of Lecture Notes in Computer Science. Springer* , 227-234.

Gao, W. C. (2004). *CAS-PEAL.* Retrieved from http://www.jdl.ac.cn/peal/home.htm

Grgic, M. D. (2011). *SCface: surveillance cameras face database. Multimedia Tools Appl. 51, 3, 863-879.* Retrieved from http://www.scface.org/.

Hailong, Z. a. (2009). Combining wavelet transform and orthogonal centroid algorithm for ear recognition.*2nd IEEE International Conference on Computer Science and Information Technology.*

Hajsaid, E. A. (2008). Ear segmentation in color facial images using mathematical morphology. *6th IEEE Biometric Consortium Conference (BCC).*

Iannarelli, A. (1989). *Ear Identification, Forensic Identification Series. .* Paramount Publishing Company, Fremont, CA.

Islam, S. B. (2008). A fully automatic approach for human recognition from profile images using 2D and 3D ear data. *4th International Symposium on 3D Data Processing Visualization and Transmission.*

Jain, A. R. (2004). An Introduction to Biometric Recognition. *IEEE Trans. Circ. Syst. Video Technol. 14, 1* , 4–20.

Kisku, D. R. (2009). SIFT-Based ear recognition by fusion of detected key-points from color similarity slice regions. *IEEE International Conference on Advances in Computational Tools for Engineering Applications (ACTEA).* , (pp. 380–385.).

Kumar, A. a. (2007). Ear authentication using log-gabor wavelets. *In SPIE Defense and Security Symposium. Vol. 6539.*

Kumar, A. a. (2012). Automated human identification using ear imaging. *Pattern Recogn. 45, 3,* 956-968.

Moreno, B. S. (1999). On the use of outer ear images for personal identification in security applications. *33rd IEEE International Conference on Security Technology*,(pp. 469 476).

Mu, Z. Y. (2004). Shape and structural feature based ear recognition. *5th Chinese Conference on Biometric Recognition*,(pp. 663–670).

NCKUDB. (n.d.). *Databases for Face Detection and Pose Estimation(National Cheng University of Taiwan Ear Database.).* Retrieved from http://robotics.csie.ncku.edu.tw/Databases/FaceDetect_PoseEstimate.htm

Phillips, P. J. (1998). The feret database and evaluation procedure for face recognition algorithms. *Image Vis. Comput. 16, 5*, 295–306.

Prakash, S. a. (2011). An Efficient Ear Recognition Technique Invariant to Illumination and Pose. *Telecommunication Systems Journal, special issue on Signal Processing Applications in Human Computer Interaction.30,* 38-50.

Prakash, S. J. (2009). A skin-color and template based technique for automatic ear detection. *7th IEEE International Conference on Advances in Pattern Recognition (ICAPR).*

Raposo, R. H. (2011). UBEAR: A dataset of ear images captured on-the-move in uncontrolled conditions. . *Computational Intelligence in Biometrics and Identity Management IEEE Workshop.*, (pp. 84-90).

Raut, S. a. (2014). Review of Biometrics: Palm Vein Recognition System. *IBMRD's Journal of Management & Research 3, 1,* , 217-223.

Sana, A. a. (2007). Ear biometrics: A new approach. . *6th International Conference on Advances in Pattern Recognition.*

UMIST. (2014). *Face Database. (University of Sheffield).* Retrieved from http://www.sheffield.ac.uk/eee/research/iel/research/face

UND. (2014). *CVRL DATA SETS (University of Notre Dame UND database),.* Retrieved from http://www3.nd.edu/~cvrl/CVRL/Data_Sets.html

USTB. (2014). *Ear Recoginition Laboratory(University of science and technology Beijing USTB database).* Retrieved from http://www1.ustb.edu.cn/resb/en/index.htm

Wang, Y. M. (2008). Block-Based and multi-resolution methods for ear recognition using wavelet transform and uniform local binary patterns. *19th IEEE International Conference on Pattern Recognition (ICPR)*,(pp. 1–4).

Watabe, D. S. (2008). Ear biometrics using jet space similarity. *IEEE Canadian Conference on Electrical and Computer Engineering (CCECE).*

Xiaoxun, Z. a. (2007). Symmetrical null space lda for face and ear recognition. *Neuro Comput. 70, 4-6*, 842–848.

XM2VTS. (2014). *The Extended M2VTS database.* . Retrieved from http://www.ee.surrey.ac.uk/CVSSP/xm2vtsdb

Yan, P. a. (2005). Empirical evaluation of advanced ear biometrics. . *IEEE Conference on Computer Vision and Pattern Recognition (CVPR).*

Yan, P. B. (2005). ICP-Based approaches for 3D ear recognition. *In Proc. SPIE, Biometric Technol. Hum. Identif. I*,(pp. 282–291).

Yuan L. and Zhang, F. (2009). Ear detection based on improved adaboost algorithm. . *8th IEEE International Conference on Machine Learning and Cybernetics (ICMLC).*

Yuizono, T. W. (2002). Study on individual recognition for ear images by using genetic local search. *IEEE Congress on Evolutionary Computation (CEC)*,(pp. 237–242).

Zhou, J. C. (2010). Histograms of categorized shapes for 3D ear detection. . *IEEE Conference on Biometrics: Theory, Applications, and Systems (BTAS).*