Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 65 (2015) 529 – 537

Procedia Computer Science

International Conference on Communication, Management and Information Technology (ICCMIT 2015)

Human Ear Recognition Using Geometrical Features Extraction

Asmaa Sabet Anwar[a,d], Kareem Kamal A.Ghany[b,d,*], Hesham Elmahdy[c]

[a]Faculty of Computers and Information, Cairo University, Cairo, Egypt
[b]Faculty of Computers and Information, Beni-Suef University, Beni Suef P.O.Box 62111, Egypt
[c] Faculty of Computers and Information, Cairo University, Cairo, 12613 Cairo University Post offices, Egypt
[d]ISI Research Lab - www.isirlab.net

Abstract

The biometrics recognition has been paid more attention by people with the advancement of technology nowadays. The human ear is a perfect source of data for passive person identification. Ear seems to be a good candidate solution since ear is visible, their images are easy to take and structure of ear does not change radically over time. Ear satisfies biometric characteristic (universality, distinctiveness, permanence and collectability). In this paper we presented a new algorithm for ear recognition based on geometrical features extraction like (shape, mean, centroid and Euclidean distance between pixels). Firstly, we made a pre-processing phase by making all images have the same size. Then we used the snake model to detect the ear, and we applied median filter to remove noise, also we converted the images to binary format. After that we used canny edge and made some enhancement on the image, largest boundary is calculated and distance matrix is created then we extracted the image features.
Finally, the extracted features were classified by using nearest neighbor with absolute error distance. This method is invariant to scaling, translation and rotation. The experimental results showed that the proposed approach gives better results and obtained over all accuracy almost 98%.

Peer-review under responsibility of Universal Society for Applied Research

Keywords: Human Ear Biometrics; Ear Recognition; Geometrical Feature Extraction; Snake Model; Passive Person Identification.

* Corresponding author. Tel.: +2-012-210-78191; fax: +2-082-224-6896.
E-mail address: kareem@bsu.edu.eg

Peer-review under responsibility of Universal Society for Applied Research
doi:10.1016/j.procs.2015.09.126

1. Introduction

Biometric has lately been receiving attention in popular media. Biometric deals with identification of individuals based on their physiological or behavioral characteristics. It is widely believed that biometric will become a significant component of the identification technology[1].

Biometrics can be divided into two classes physiological and behavioral. Physiological which are based upon measurements of external physical traits, such as weight, height, body shape, face shape, hand shape, skin color, texture, odor, hair color, retina, iris, Deoxyribonucleic Acid, fingerprint and ear shape. Behavioral which usually measure learned behaviors, such as gait, body posture, speech, handwriting, keyboard typing pattern, heartbeat, respiration pattern, and eye blinking pattern[2].

Any human physiological or behavioral characteristic could be a biometrics if it has the following properties[3]:

(1) Universality, which means that every person should have it.

(2) Uniqueness, which indicates that no two persons should behave the same characteristic.

(3) Permanence, which means that this characteristic does not change over time.

(4) Collectability, which indicates that the characteristic can be measured quantitatively.

Biometric system can be used in two modes: verification or identification. Identification involves comparing the information against templates corresponding to all users in the database. This take much time because this depending on size of database. Verification involves comparison with only those templates corresponding to the claimed identity. This not takes much time because this compares one to one. This implies that identification and verification are two problems that should be dealt separately[3].

There are many advantages of using the ear as a source of data for human identification. Firstly, ear does not change considerably during human life. Secondary, Ears have both reliable and robust features which are extractable from a distance. Thirdly, Ear prints could be printed at a scene of crime. There are some challenges to the use of the ear to identify people, including hair on the ear that obscures a large part of them, headscarf worn by Muslim women to cover their hair therefore cover their ears and the level of illumination.

The rest of the paper is organized as follows, section 2 discusses the related work, section 3 describes the proposed approach and its phases, section 4 presents the experimental results, and finally conclusion and future work are provided in section 5.

2. Related work

Many approaches and several researches have been proposed to extract unique features from human ear to identify people depend on this features.

Zhichun Mu et. al[4] discussed the edge-based ear recognition method including ear edge detection, ear description, feature extraction, recognition method and ear database construction. The feature vector is composed of two vectors: inner and outer vectors. They constructed ear database which composed of 77 subjects. The images of each subject are taken under two conditions: illumination variation and orientation variation. Individuals were invited to be seated 2m from the camera and change his/her face orientation. The images size is 300x400 pixels. Using the Back Propagation network as classifier, they got a recognition accuracy of 85%. Accuracy is still low.

JitendraB et. al[5] produced multiple geometrical feature extraction (such as shape, Euclidean distances of side of a triangle, and angles of a triangle as a feature vector) of ear based method to identify a person using ear biometrics.
They used their own database. The side face images are acquired using digital camera under lighting conditions with no illumination change. Data of 30 people tests have been conducted, successful results were found for 28 subjects with overall efficiency of 90%, but they used very small database.

AnupamSana et. al[6] presented ear biometrics system for human recognition based on Haar wavelet transform. Haar wavelet transform was used to decompose the ear image and compute coefficient matrices of the wavelet which were clustered in its feature template. Decision was made by matching one test image with n trained images using Hamming distance approach. They used two databases IITK and database created from Saugor University, India. Accuracy of the system is 96%. Coefficient matrices were very large.

Choraset. al[7] also used an approach for feature extraction based on contour detection, but disadvantage of this method is erroneous curve detection. They performed their experiments on their database of collected ear images (240 images). They divided the database into several sets of images concerning their quality and degree of complexity. They limited their experiment with images of very high quality. For such easy images from their database they obtained error-free recognition.

Chang et. al[8] used Principal Components Analysis which is the most popular approaches to ear recognition. Their database used consisted of 197-images as a training set. But this approach gives very low accuracy 71.5%.

Wang et. al[9] used moment invariants and Back Propagation neural network. Their database used consisted of 60 images and accuracy=91.8%. Database is small.

3. The Proposed Approach

Traditional methods for personal identification are based on what is the person know like PIN's, passwords, identification cards, and specific keys. These methods have a lot of disadvantages like hard to remember, easy to lose, lack of security, cards and keys are often stolen and passwords can be cracked. Because of disadvantage of traditional methods for identification we preferred to use biometrics. Biometrics has lately been receiving attention in popular media. Biometric deals with identification of individuals based on their physiological or behavioral characteristics. It is widely believed that biometrics will become a significant component of the identification technology. Ear seems to be a good candidate solution in human identification since ear is visible, their images are easy to take and structure of ear does not change radically over time.

The proposed approach consists of: Pre-Processing, ear detection, edge detection, post processing, feature extraction and finally classification as discussed below and shown in **Fig. 1.**

3.1. Pre-processing

In this phase, we resized images to [272 X 204] pixels according to be the same as the size of images in database. We smoothed image using Gaussian filter as shown in the following equation:

$$G(x,y) = (1/2\pi\sigma^2)\, exp^{-(x^2+y^2)/2\sigma^2} \tag{1}$$

Where x and y are the image pixels coordinate, σ is the standard deviation.

3.2. Ear detection

3.2.1 Use snake model to detect the object in an image[10].
3.2.2 Select manually the initial position of the snake by clicking on the image and selecting control points.
3.2.3 Specify various control parameters for the snake as follows:
α (alpha): Specifies the elasticity of the snake. This controls the tension in the Contour by combining with the first derivative term.
β (beta): Specifies the rigidity in the contour by combining with the second derivative term.
γ (gamma): Specifies the step size.
κ (kappa): Acts as the scaling factor for the energy term.
W (Eline): Weighing factor for intensity based potential term.
W (Edge): Weighing factor for edge based potential term.
W (Eterm): Weighing factor for termination potential term.

3.2.4 Specify the number of iterations for which contours position is to be computed.
3.2.5 Use default values as follows:
Alpha =0.40, beta =0.20, gamma =1.00, kappa =0.15, W (Eline) =0.30, W (Edge) =0.4, W (Eterm) =0.70 and iteration=200.

3.3. Edge detection

In this phase, we applied median filter with size 5x5 to remove noise. Then we transformed image into binary image by using Global Threshold. After that Canny edge detector would be used to find edges by looking for local maximum of the gradient of I. The gradient is calculated using the derivative of a Gaussian filter. This method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges.

3.4. Post-processing

In this phase, we applied some morphological operations like dilate as in equation (2) to connect edges that can break throw edge detection. Then remove unwanted object that less than 50 pixels. After that we used equation (3) to close the contours.

$$X \oplus H = \cup_{h \in H} X_h \tag{2}$$

$$X \cdot H = (X \oplus H)\, \theta\, H \tag{3}$$

Where H is the structure element, and X is the image.

3.5. Feature extraction

In this phase, we get boundary of binary images, detect largest object, and get minimum Euclidean distance between every pixel and all pixels as shown in equation (4). Finally we sorted the matrix containing all distance descending, four distances are taken, First distance D (1) mean first value in distance matrix (largest one), Distance2 is another value in distance matrix and so on. Centroid of largest object and mean of ear image are also taken as feature values to ensure uniqueness between ear images.

To clarify our selection, firstly we selected the maximum value between pixels only and we get poor results. Then we try to add another value to the selected one to improve the accuracy. And to make an appropriate space between values we divide values by 2, 3, and 4.

$$D\big((x_1, y_1), (x_2, y_2)\big) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{4}$$

Where D is distance between two pixels with coordinates (x_1, y_1) and (x_2, y_2)

For summarization, feature vector consist of seven values:

- Distance 1 (D(1))
- Distance 2 (D (Size(D) / 2)
- Distance 3 (D (Size(D) / 3)

- Distance 4 (D (Size(D) / 4)
- X coordinate of centroid
- y coordinate of centroid
- Mean is calculated as shown in equation (5)

$$X = 1/N \sum x_i \quad (5)$$

Where *X* is mean of the image and *N* is number of pixels.

3.6. Classification

We will use three types of classifiers which are Naive classifier, nearest neighbor (distance type: Euclidean) and K nearest neighbor (distance type: minimum absolute difference). We will explain the difference between classifiers in terms of accuracy in the experimental results section.

$$D(x,y) = \sum_1^n |(x_i - y_i)| \quad (6)$$

Where *x*, *y* are the coordinate of image pixels and *n* is number of pixels in image.

Algorithm 1. Proposed Approach Algorithm.

1) Read original image I(i , j)
2) Resize image to 272x204 according to size of images in database
3) Smooth image with Gaussian filter
4) Detect ear using snake model
5) Convert Region of interest polygon (ear image) to region mask M(I, i)
6) Isolate Ear image only ear(I,j)= I(I,j) .* M(I,j)
7) Apply median filter
8) Convert ear image to binary image based on threshold
9) Apply canny edge detector
10) Dilate ear image to connect edges that can broke throw edge detection.
11) Remove small object which consider it as noise
12) Try to close contours
13) Get all boundaries of all objects in binary image
14) Detect largest object
15) Compute Euclidean distance between every pixel and all pixels in the ear image as shown in equation(4)
16) Sort distance D descending
17) Take maximum value and three other distance as feature values to ensure uniqueness between ear images
18) Get mean of ear image as feature value
19) Get centroid of largest object as feature value
20) Feature vector consist of 7 values
    - Distance 1 (D(1))
    - Distance 2 (D (Size(D) / 2)
    - Distance 3 (D (Size(D) / 3)
    - Distance 4 (D (Size(D) / 4)
    - X coordinate of centroid
    - y coordinate of centroid
    - Calculate Mean using equation(5)

21) Apply K nearest neighbour to classify ear images using equation (6)

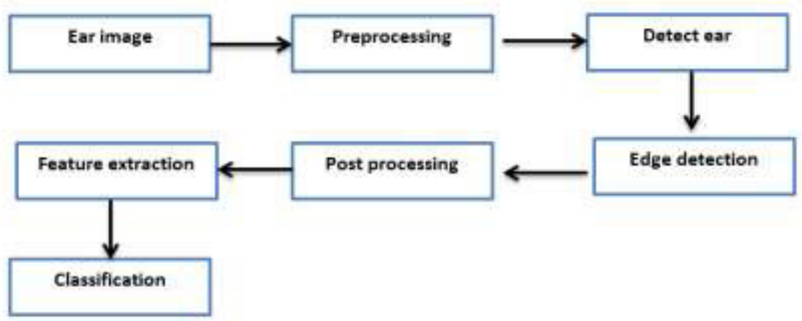

Fig. 1. Proposed Model Block Diagram.

4. Experimental results

4.1. Description of the IIT Delhi ear database version 1.0

The IIT Delhi Ear Database mainly consists of the hand images collected from the student and staff at IIT Delhi, India. This database has been acquires during Oct 2006 Jun2007 using a simple imaging. Database is taken from group which ages are between 14 and 58 years. The resolution of these images is 272x204 pixels. We can see sample form this database in **Fig. 2.**

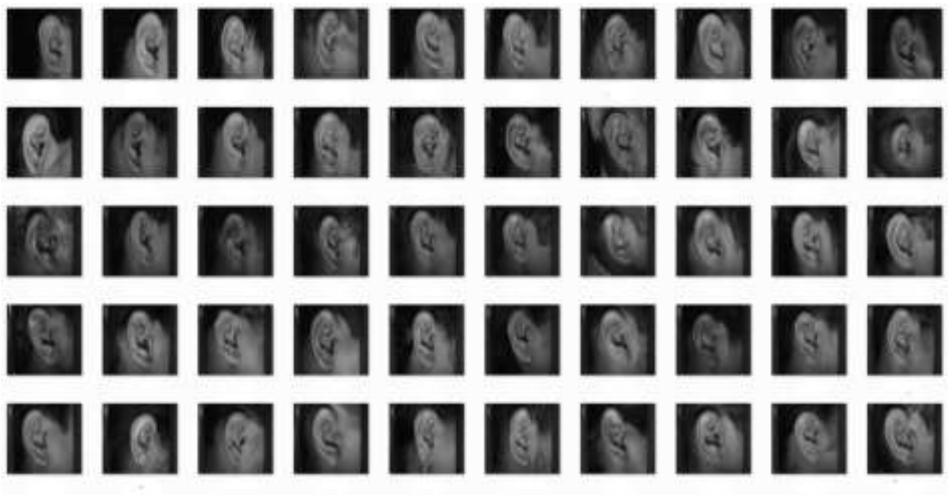

Fig. 2. Sample of images in IIT database.

4.2. Results and discussion

We used sample of IIT database, 3 ear images for 50people. Also we used 2 images for training and 1 image for testing (100 images as training, 50 images as testing).

In this experiment we used sample of IIT database, 3 ear images for 50 people. Used 2 images for training and 1 image for test, then training images =100 images and testing images =50 images. The sequence of algorithm output is shown in **Fig. 3.** Classification step done using more than classifier but one nearest neighbor with sum of absolute difference distance which give the highest accuracy, Images classified true=49 and Images classified false=1 Then Accuracy= 98% when used sum of absolute distance in K nearest neighbor classifier as shown in **table 1**.

Table 1. Classifiers used and accuracy

Classifier	Accuracy
Naïve	*88%*
Euclidean distance	*94%*
Sum of absolute difference	*98%*

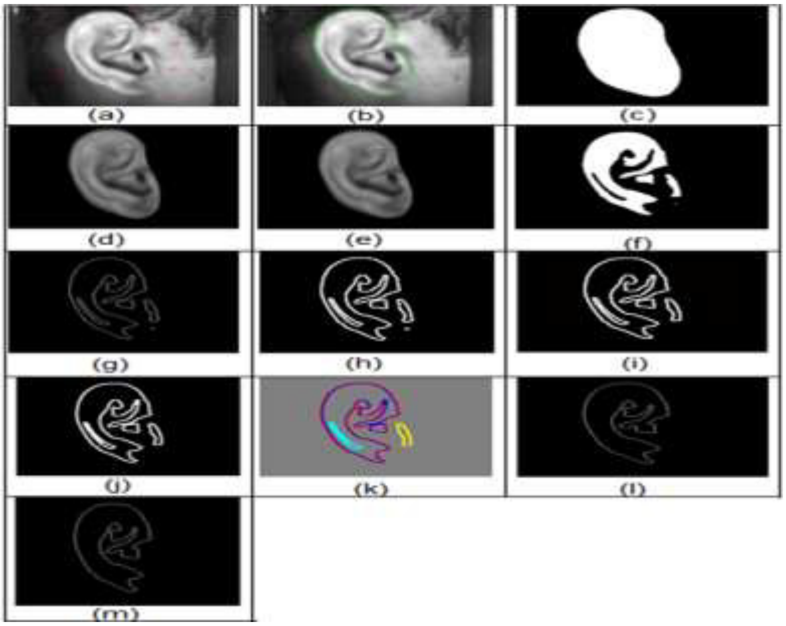

Fig. 3. The result of pre-processing, ear detection and extract feature. (a)Initialization point of snake model. (b)Output of snake model. (c)Mask of region of interest. (d)Isolated ear image. (e)Apply median filter. (f)Converting to binary image with threshold 0.4. (g)Canny edge detection. (h)Ear after dilatation. (i)Remove object ≤50 pixel. (j)Close contour. (k)Detect largest object. (l)Separate largest object. (m)Centroid point in red.

We made a comparison between researchers worked in this topic according to accuracy and number of images used in database. We can notice that most of researchers used their own database not standard databases. This may cause bad results because using standard databases enable us to compare our results with it. In addition the researchers' databases are small like in [5] authors used 30 images only and the accuracy is equal to 90 %, in [11] they used 58 ear images and the accuracy is equal to 87.9%. Finally, in[16,17] authors used IIT Delphi and they achieved good accuracy but less than our work. **Table 2 and Fig. 4.** Clarify these results.

Table 2. Classifiers used and accuracy

Publication	Approach	Name of Database	Ear database	Accuracy
Jitendra.B[5]	Geometrical feature	Their Own Database	*30*	*90%*
Abdel-Mottaleb and Zhou[11]	Modified force field transform	Their Own Database	*58*	*87.9 %*
Yaqubi et al. [12]	HMAX and Support Vector Machine	USTB	*180*	*96.5 %*
Alaraj et al. [13]	Principal Components Analysis with MLFFNNs	Their Own Database	*85*	*96 %*
Wang et al. [9]	Moment invariants and Back Propagation neural network	Their Own Database	*60*	*91.8 %*
Mu Zhichun et al. [4]	Geometrical features (LABSSFEM)	Their Own Database	*144*	*85 %*
Belé Moreno et al. [14]	Neural Networks	Their Own Database	*168*	*93 %*
Chang et al. [8]	Principal Components Analysis	ND Human ID	*285*	*71.6 %*
Wang et al. [15]	Moment Invariants	USTB	*180*	*96 %*
Anam Tariq et al. [16]	Haar Transformation	IIT	*375*	*95.2%*
Murukesh.C et al. [17]	Contoulet and PCA	IIT	*50*	*96%*
This Paper	**geometrical features**	**IIT**	***150***	***98 %***

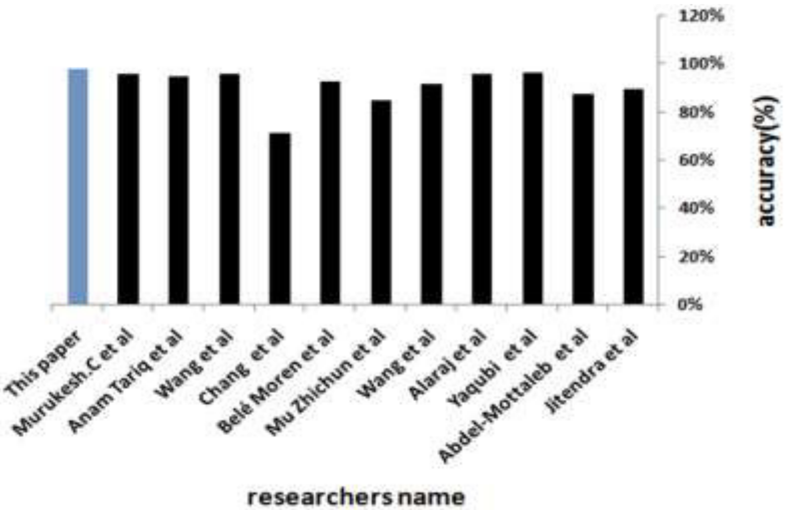

Fig. 4. Comparing the accuracy of our work with other researchers

5. Conclusion and future works

We proposed a new algorithm for ear recognition based on geometrical features extraction. Seven values are extracted as feature vector which are mean of ear image, centroid of x coordinate, centroid of y coordinate, four different distances from matrix which contain Euclidean distance between every pixels in image. We tried to increase the distance values were taken to increase the feature vector which will be more representative. We not effect on the run time because the feature vector is still small but representative. K-nearest neighbor used for classification because this classifier gives higher accuracy. The experimental results showed that the proposed approach gives better results and obtained over all accuracy almost 98%.

In the future work, we plan to increase the number of ear images and use more database types to evaluate the performance of the system. Also we will try to deal with challenges such as drop-down hair on the ear, which obscures part of them.

References

1. Van der Geer J, Hanraads JAJ, Lupton RA. The art of writing a scientific article. *J Sci Commun* 2000; **163**:51-9.
2. Strunk Jr W, White EB. *The elements of style* ● 3rd ed. New York: Macmillan; 1979.
3. Mettam GR ●, Adams LB. How to prepare an electronic version of your article. In: Jones BS, Smith RZ, editors. *Introduction to the electronic age* ● New York: E-Publishing Inc; 1999. p. 281-304.

1. Burge M, Burger W. Ear Biometrics. In: Jain AK, Bolle R, Pankanti S, editors. Biometrics: *Personal Identification in Networked Society*. Springer; 2013. p. 273-286.
2. Hurley D J. Force Field Feature Extraction for Ear Biometrics. Ph.D Thesis. University of Southampton. 2001.
3. Delac K, Grgic M. A Survey of Biometric Recognition Methods. In Proceeding of Elmar. The 46th International Symposium. Croatia; 2004 p. 184-193.
4. Mu Z, Yuan L, Xu Z, Xi D, Qi S. Shape and Structural Feature Based Ear Recognition. Lecture Notes in Computer Science (LNCS); 2004. 3338, p. 663-670.
5. Jawale B, Bhalchandra S. The Human Identification System Using Multiple Geometrical. *International Journal of Emerging Technology and Advanced Engineering*; 2012. 2:3. p. 662-666.
6. Sana A, Gupta P, Purkait R. "Ear Biomertics – New Approach. In Proceedings of ICPAR; 2007. p. 1-5.
7. Choras M. Ear Biometrics Based on Geometrical Feature Extraction. Electronic letters on computer vision and image analysis; 2005. 5:3. p. 84-95.
8. Chang K, Bowyer KW, Sarkar S, Victor B. Comparison and Combination of Ear and Face Images in Appearance-Based Biometrics. IEEE Transactions on Pattern Analysis and Machine Intelligence; 2003. 25:9. p. 1160-1165.
9. Wang XQ, Xia HY, Wang ZI. The Research of Ear Identification Based on Improved Algorithm of Moment Invariants. In: Wuxi JS, editors. Proceedings of Third Int. Conference on Information and Computing (ICIC); 2010. p. 58-60.
10. Jarjes AA, Wang K, Mohammed GJ. Improved Greedy Snake Model for Detecting Accurate Pupil Contour. In Proceedings of 3rd International Conference on Advanced Computer Control (ICACC); 2011. Harbin. p. 515-519.
11. Mottaleb A, Zhou J. Human Ear Recognition from Face Profile Images. In: Zhang D, Jain AK editors. *Advances in Biometrics*. Springer. Berlin/Heidelberg. Lecture Note of Computer Science (LNCS); 2005. p. 786-792.
12. Yaqubi M, Faez K, Motamed S. Ear Recognition Using Features Inspired By Visual Cortex and Support Vector Machine Technique. In Proceedings of Int. Conference on Computer and Communication Engineering (ICCCE). Kuala Lumpur; 2008. p. 533-537.
13. Alaraj M, Hou J, and Fukami T. A neural Network Based Human Identification Framework Using Ear Images. In Proceedings of TENCON 2010 Conference. Fukuoka; 2010. p. 1595-1600.
14. Moreno B, Anchez A, Vlez JF. Use Outer Ear Images for Personal Identification in Security Applications. In Proceedings of the 33rd Annual International Carnahan Conference. Madrid; 1999. p. 469-476.
15. Zhongli W, Zhichun M. Moment Invariant Based Ear Recognition. *Pattern Recognition and Artificial Intelligence Journal*; 2004. 17:4. p. 502-505.
16. Tariq A, Anjumt MA, Akram MU. Personal Identification Using Computerized Human Ear Recognition System. In Proceedings of Int. Conference on Computer Science and Network Technology (ICCSNT). Harbin; 2011. p. 50-54.
17 Murukesh C, Parivazhagan A, Thanushkodi DK. A Novel Ear Recognition Process Using Appearance Shape Model, Fisher Linear Discriminant Analysis and Contourlet Transform. In Proceedings of Int. Conference on Modelling Optimization and Computing; 2012. p. 771–778.