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Identifying a person using 2D Ear images

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***Abstract**: Authentication of a person has become one of the most essential elements of today's world. With the cyber space coming into the picture, the need to accurately authenticate a person has increased rapidly. Many biometric systems exist such as face recognition, fingerprinting, etc., but we made ear as our field of interest and came up with a way to authenticate a person using ear recognition. Ear recognition is still in its nascent stage and has a lot of potential to become either a standalone or combined biometric system.*
***Keywords**: Ear recognition, Ear biometrics, occlusion,*

I. Introduction

Human ears offer some distinct advantages over other biometric modalities: they have a wealth of structural features that are permanent with increasing age from about 8 to 70 years old, and they are not affected by the expression variations. Ear features have been used for many years in forensic science recognition. Ear is a stable biometric and does not vary with age as compared to face structure. Ear has all the propertied that a biometric trait should have .i.e. uniqueness, universality, permanence and collectability. Current ear recognition approaches have exploited how to use 2D ear image and 3D ear model for human identification. At present, 3D ear recognition performs well in illumination variation or pose variation, but it needs expensive computation and special equipment's. Most of the recent works on ear recognition are focused on 2D images because using 2D images is more consistent with deployment in surveillance or other planar image scenarios. Recent research on ear recognition in 2D can be categorized as follows: ear recognition under controlled environment, ear recognition with pose variation and ear recognition under partial occlusion. In constrained environment, the proposed ear recognition methods perform well. But in real applications, human ears will be occluded in some scenarios. So ear recognition under occlusion, pose variation or with noised images are unavoidable problems.

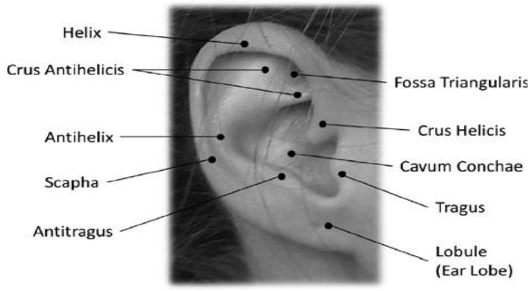
II. Problem Definition

Biometrics is one of the leading ways of authenticating a person. Amidst all the biometric systems available, ear has been least explored as an option. Ear offers great benefits as a biometric system and can be used in combination with other biometric system like face recognition for enhanced accuracy. The characteristics responsible for making ear popular as a biometric system are the fact that ear recognition is non-intrusive, it doesn't change with age or expression, it has great potential to be used in combination with other biometric systems, etc. Even after so many favorable properties being possessed by ear with regards to it being a biometric system, the research in this field has been fairly limited. The Principal Component Analysis based approach has been widely used in face recognition. We bring that same approach to ears. In this paper, we come up with an ear recognition technique using Principal Component Analysis.

A. Anatomy of EAR

Ear does not have the complete structure.it has the standard parts as other biometric trait has i.e. face. Unlike human faces ear has no expression changes, make-up effects and more over the color is constant throughout the ear as the age changes. Ear is also non-intrusive and does not need the person to sit with the same expression like in face recognition, it also does not cause any sort of discomfort to the person, like in the case of finger print scanner and DNA testing. The basic anatomy of the ear is given below and it shows all the major parts of an ear that are visible from the outside. We are using both the internal as well as the external edges of the ear to determine if the ear belongs to the person or not. We have made use of 2 feature vectors that are later used to classify an image based on the database that we have acquired.

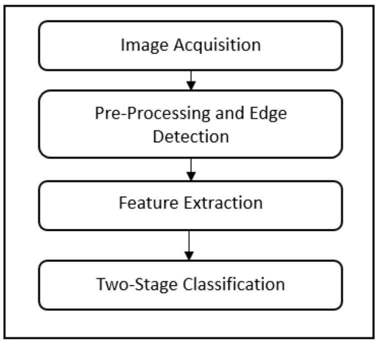
Fig. 1. Anatomy of the EAR



III. Major steps of EAR recognition

The Fig. 2. Shows the major steps and the block diagram of the ear recognition system.

Fig. 2. Block Diagram Of the system



A. Image Acqustion

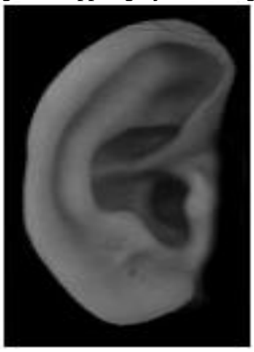
The side face images have been acquired in the same lightening conditions. All Images taken from with a distance between the ear and camera is 15-20 cms. The image should be carefully taken such that outer ear shape is preserved. The less errors in the outer shape the more accurate results are shown in the Fig 3.

Fig. 3. A side face image acquired

B. Preprocessing and Edge Detection

Using segmentation the ROI of the image is selected. Color image is then converted to grayscale image. The converted grayscale image is shown in the Fig. 4

Fig. 4. Cropped grayscale image



C. Edge Detection and Binariztion

Canny Edge Detection Algorithm is used for edge detection and binarization. If w is the width of the image in pixel and h is the height of the image in pixel, the canny edge detector takes as input an array $w \times h$ of gray values and sigma (standard deviation).Output is a binary image with a value 1 for edge pixels, i.e., the pixel which constitute an edge and a value 0 for all other pixels. Fig. 6. Shows the grayscale and edge detected binary image. The noise is removed from the image by using adaptive median filter. Fig. 7. Shows the images with and without noise.

Fig. 6. Grayscale image its corresponding edge detected binary image

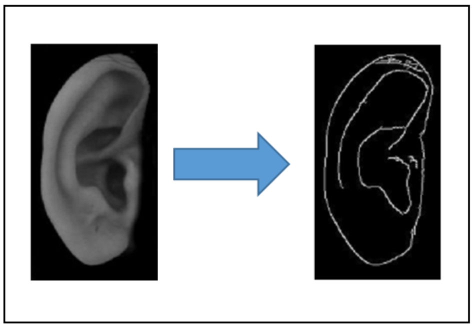
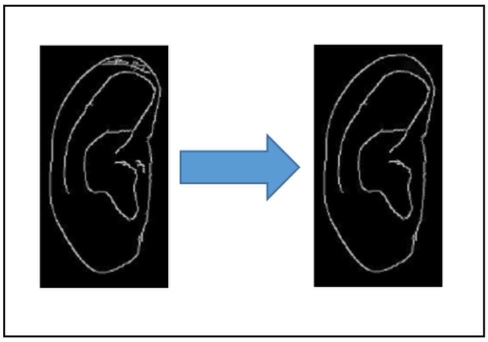


Fig. 7. Images with and without noise



Canny Edge Detection Algorithm

Step 1: Smoothing: - For removing the noise from the image make it blur.

Step 2: Finding Gradient: - Mark the image so that the gradients with large magnitude can be located. The gradients show the change in the intensity, which indicate the presence of the edges. Gradients in X-direction and Y-direction is obtained.

Step 3: No- maximum suppression: - Edges will occur at points where the gradient is at a maximum. Therefore the non-maximum points must be suppressed.

Step 4: Thresholding: - Potential edges are determined by thresholding.

Step 5: Hysteresis: - The method of thresholding is called as hysteresis. It makes the use of the high and the low threshold value. That is if the pixel has the value above the high threshold it is as the edge pixel. That is if the pixel has the value above the low threshold and is the neighbor of an edge pixel, it is set as an edge pixel. Otherwise the pixels are not the edge pixel.

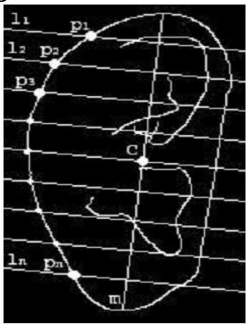
D. Feature Extraction

In this stage the features extraction is done in all the angles of the image. The features extracted are divide in two vectors. Using the outer shape of the ear First vector feature is found. All the other remaining edges are found using Second feature. The concept of the terms max-line and normal line are used to find the angles.

Max-Line: It is the longest line that can be drawn with both its endpoints on the edges of the ear. The length of line is measured in terms of Euclidean distance. If there are more than one line, features corresponding to each max-line are to be extracted.

Normal Line: Lines which are perpendicular to the max-line and which divide the max-line into the (n+1) equal parts, where n is the positive integer. Fig. 8.shows the image with the max-line and normal line.

Fig. 8. Image with max-line and normal-line.

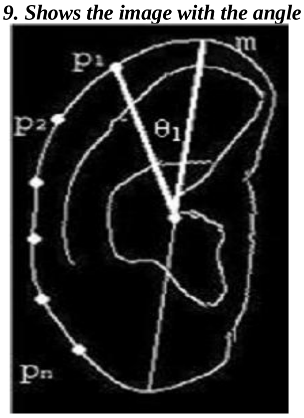


The max-line m, normal line $l_1, l_2, l_3, \ldots, l_n$ are named from top to bottom. Center of the max-line is C. $P_1, P_2, P_3, \ldots, P_n$ are the lines that intersect the outer edges and the normal-lines.

First Feature Vector(FV1): It is defined by the following formula.

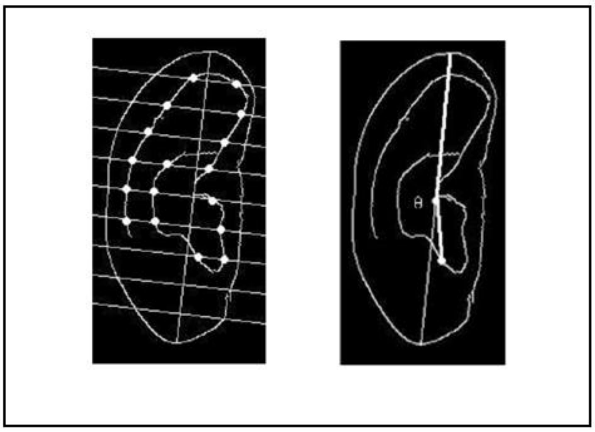
FV1=[$\theta 1, \theta 2, \theta 3, \ldots, \theta n$]

Fig 9. Shows the image with the angle $\theta 1$



Second Feature Vector(FV2): It is the vector in which all the points where the edges of the ear and the normal line intersect except the outer edge.Fig. 10. Showing the second feature vector and the angle respectively.

Fig. 10. Second feature vector and the angle



E. Classification

Classification is the task of finding a match for a given query image. Here classification is performed in two stages. In first stage the first feature vector is used while in second stage second feature vector is used.

Let *FV1 =* [$\theta 1, \theta 2, \theta 3, \ldots \theta n$], *FV2=* [$\alpha_1, \alpha_2, \alpha_{3\ldots}$ αn] be the first feature vectors of the two images which are to be matched. Using these vectors two major difference (d_1) and the number of point matched (w_1) are to be calculated

$$d1 = \sum_{i=1}^{n} |\theta i - \alpha i|$$

These two points are said to be matched if their corresponding angles are same or below the threshold value

$$w1 = \sum_{i=1}^{n} Xi$$

Where Xi=1 if threshold $|\theta i - \alpha i|$ is less than some threshold value else Xi=0

The two images are said to be matched with respect to the first feature vector if d_1 and w_1 are less than some threshold values.

In the second stage two points are to be matched if their angles are approximately same and also they correspond to the same normal line.

Let w_2 be the number of the points that are matched but as the size of the second feature vector is not fixed the percentage of the matched points is calculated by the formula given below

$$Pt = \frac{w2}{\min(V1, V2)}$$

Where *V1, V2* are the sizes of the second feature vector of the two images.

Two images are to be matched finally if they are matched with respect to the first feature vector and the point Pt is greater than some threshold value.

Advantage of two stage classification

1. A given query image is first tested against all the images in the database using first feature vector.
2. Only the images are matched in the first stage are considered for second stage of classification.
3. As the size of the FV1 is less, that is n (number of normal line) so only n comparison is needed for the first stage classification.
4. In the second stage classification m*n comparison are required, assuming m points for each normal line.
5. If the classification is single stage, than total comparison required are I*((n) + (m*n)), where I is the number of images in the database.
6. If the classification is divided into two stage the comparison would be I*n+I1*(m*n) where I1 is the number of image that are matched with respect to the first feature vector.
7. Saved computation is (I – I1)*(m*n).

IV. Conclusion

The Eigen face approach for recognition was first proposed by Turk and Pentland. They used PCA to create an Eigen space for all subjects in the database. Our approach takes this idea and applies it to the problem of ear recognition. We have managed to create an ear biometric system which matches the test ear with the other ear images in its database based on the algorithm. Our database has 7 images of 29 people in our database, which we have obtained from UND. We are using 5 images to train the PCA and the rest two as the test images. Testing the system manually, we found that the accuracy rate is 90% when it comes to the test images of the people who are in the database. Testing the system with images of people not present in the database gave us the manually calculated FAR of 20%. We have also managed to create our own database by taking pictures of our group members and cropping them to the desired dimensions. We would be working at a greater depth in this field. We are currently researching on implementing this idea at a more robust and dynamic level with an improved user interface. We are working on taking this approach to the 3D level and also researching on real-time applications of the system.

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