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Human Identity Recognition Using Ear Lobes Geometric Features

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Abstract: ***Verification of person by means of Biometrics can be uniquely identified by one or more biological traits of that person. These unique identifiers include eye pattern, hand pattern, fingerprints, earlobe geometry, retinas, DNA, voice waves and signatures. Recent research in biometrics field has done into finding more ways to identify someone through different gaits proposed. Among many, earlobe biometrics is the stable one considered in the light of aging of Human bodies. As others earlobes geometry does not change with time and emotions. Geometric features considered in earlobe biometrics are ears height, corresponding angles, and inner ears curve and reference line cut points. Random orientation is performed and it shows greater accuracy than previous model. The recognition accuracy is increased by training images in databases. This class of passive identification is ideal for biometrics because the features are robust and can be reliably extracted from distance.***

Keywords: ***Edge Detection, Nearest Neighbor, Geometric Features, KNN Algorithm, Blob Detection algorithm***.

1. Introduction

Recognition of individuals based on biometric systems is so rapidly developing. The biometrics system does consistent recognition by discovering the physical or behavioral characters of human beings. These are unique on all living personnel. Biometric systems deployed enhance the security, reliability and efficiency in identification process. Based on distinctiveness and steadiness of the biometrics during human's lifespan, it is easier to recognize and authenticate. Earlobe biometrics is new class of biometric with enviable features are universality, uniqueness and immovability. Ear has vital features, it is having constant structure which do not change with time period (age). It doesn't change shape with expressions, cosmetics and hair dressing.

In this paper, we present canny edge detection method to recognize the earlobes inner and outer borders and eliminating the noisy data from the captured image. To contest the input edge image with the present database, we present KNN algorithm to validate the exact image for the given input data. Making input edge image as centric and find the related or nearest edge image from the Database. Using centric method it matches the images based on the inner and outer edge locations from the ear images. It gives effective toning technique to identify the edges and it increase the accuracy of ear recognition. Database is having the all the images with their respective inner and outer edge locations in the form of images. Ear recognition gives effective and uniqueness to authenticate the person without any changes in future. Even though ear biometrics have not been implemented commercially so far, there are some known methods of feature extraction from ear images.

2. Existing Model

The existing models that are currently present in the domain are Infrared Rays, Sonar Based Systems and various 3D Modelling are applied. Mark Burge et al and Wilhelm Burger et al [1] introduced a model for authentication for biometrics for erroneous curve segments. The medical report [2] shows that variation over time is most noticeable during the period from four months to eight years old and over 70 years old. Due to the ear's uniqueness, stability, and predictable changes, ear features are potentially a promising biometric for use in human identification [3], [6], [5], [4]. Experiment with three neural net approaches to recognition from 2D intensity images of the ear. Their testing uses a gallery of 28 people plus another 20 people not in the gallery. They find a recognition rate of 93 percent for the best of the three approaches. They consider three methods (Borda, Bayesian, and weighted Bayesian combination) of combining results of the different approaches but do not find improved performance over the best individual method.

An "eigen-ear" approach on 2D intensity images for ear biometrics has been explored by Victor et al. [5] and Chang et al. [6]. The two studies obtained different results when compared with the performance of facial biometrics. The ear and the face showed similar performance in Chang's study, whereas ear performance is worse than the face in Victor's study. Chang suggested that the difference might be due to the differing ear image quality in the two studies. Yuizono et al. [7] implemented a recognition system for 2D intensity images of the ear using genetic search. In their experiments, they had 660 images from

110 people with six images per person. The images were selected from a video stream. The first three of these are used as gallery images and the last three are probe images. They reported that the Recognition rate for the registered people was approximately 100 percent and the rejection rate for unknown people was 100 percent.

A. Maintaining the Integrity of the Specifications

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3. Proposed Model Along with Algorithms

In Biometric, Ear recognition is the one of the interesting approach to identify the person's identity. Identifying the person from image is difficult and even the various identity methods are the finger print sensors and the retina scans but they are mostly difficult to implement as the user has to introduce the finger and the eyes in the case of the retina scan identification.

Preliminary stages gather the N number of ear images respected to person and are stored in the database. Storage of input images is done using scanning, gray scale conversion method, median filter and canny edge detection methods. Image acquisition is the main step to capture and position the image in a proper way. At first the image is captured with the help of the camera device and convert into gray scale image. After that remove the noise in image and find mean vale of image. Using canny edge detection mechanism recognize the inner and outer edges they are stored in the database. To identify input image, these image edges are identified and treated as "k". Using K-Means method match the edge image with database images and find the nearest image to the given input image find the exact image with that process to successfully recognize user details and provide authentication. Canny edge detection algorithm runs in five steps: Smoothing, Finding gradients, Non-maximum suppression, Double thresholding and Edge tracking by hysteresis. KNN method used to find the exact image to the given image with respect to the person authentication. KNN is related to clustering mechanism. Here specific image acts as centroid and perform the matching method finding nearest neighbor mechanism and gives the proper recognition.

1. Scanning Ear Image

This is the initial step that involves scanning of the given image. In this we are scanning the earlobe image and storing that image in our database for further purpose. It is treated as original image.

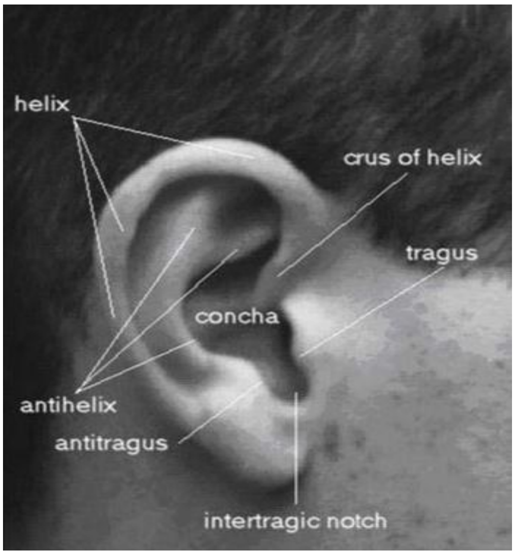

Figure 1: Ear Edges Image

2. RGB Image Converting To Grey Scale Format

RGB encoding of pure red is (255, 0, 0), pure green is (0, 255, 0) and pure blue is (0, 0, 255). In all RGB encodings, the first value is the amount of red, the second value is the amount of green and the third value is the amount of blue. These three colours are considered in RGB model. The range of the three numbers is starting from 0 to ending 255.Gray scale images are in black, white, and all the shades of grey are available. The RGB encoding of any grey values is a set of three equal numbers, i.e., (x, x, x), where x is some integer between 0 and 255. Next step is to converts the full-colour image to an 8-bitrepresentation. This reduces space complexity, making further evaluations faster without losing any reliability.

3. Canny Edge Detection Method

The canny edge detection method segregate earlobes inner and outer layer edges from the captured image. This gives the required edges of earlobe. So, using this mechanism we can find the exact earlobes edge boundaries to identify the image and also the authentication process will be easy. Canny edge detection algorithm runs in five steps: Smoothing, Finding gradients, Non-maximum suppression, Double thresholding and Edge tracking by hysteresis.

3.1 Smoothing

Initially images is captured form camera and those images have some amount of noise data. So in the early stage only images are smoothed by processing them through Gaussian filter. Data loss in this step is negligible which helps in upcoming steps of canny edge detection method. Smoothed images are noiseless bot not suited for direct classification so method goes through further steps as to make image flawless.

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3.2 Finding gradients

These areas are found by determining gradients of images. After smoothing process find the gradient points, which determine each pixel by applying Sobel operator. Initially the step is to estimate the gradient in the x- and y-direction correspondingly by applying the kernels. The gradient magnitudes are also call as edge strengths, can then be determined as Euclidean distance measured by applying the law of Pythagoras as shown in Equation (1)

a. Sometimes it is easy by applying Manhattan distance measure shown in Equation.

$$G = \sqrt{G_x^2 + G_y^2} \quad (1)$$

Where, Gx= gradients in the x-direction and Gy are the gradients in the y-directions respectively.

Gradient magnitude determines edges with respect to an image clearly. Though, the edges are typically broad and do not indicate precisely where the edges are. The direction of the edges must be determined and stored as shown in Equation (2).

$$\Theta = \operatorname{atan2}(G_y, G_x) \quad (2)$$

3.3 Non-maximum suppression

This focuses on converting blurred image of gradient magnitudes to sharp images which are lossless and they are helpful in determining the steps of double thresholding and Edge Tracking by Hysteresis. Essentially this is done by preserving all local maxima in the gradient image, and removing unnecessary data in the image as shown in below steps:

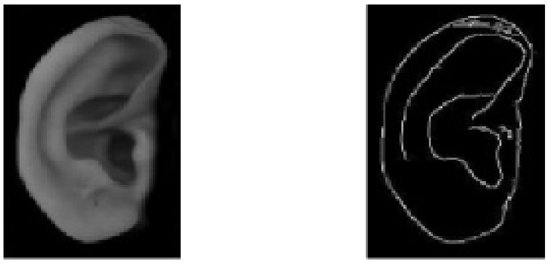
1. Round the gradient Direction θ to nearest coordinate, equivalent to the use of an 8-connected vicinity.
2. Contrast the edge strength of the existing pixel with the edge strength of the pixel in the optimistic and pessimistic gradient direction.
3. If the edge strength is large for current pixel, then conserve value of the edge strength and if not stem the value.

3.4 Double Thresholding

The edge pixels lasting after the non-maximum suppression step are striking with their strength pixel-by-pixel. Those pixels will possibly be true edges in the image, but some may cause noise or color variations for graphic due to rough surfaces. To differentiate these pixels, use threshold values then only strongest edge value will conserved. These edge pixels are strong when it has high threshold and weak when they have low threshold.

3.5 Edge tracking by hysteresis

Edge tracking can be determined by BLOB-analysis (Binary Large Object). Using 8-connected neighborhood it connect to BLOB's. BLOB's should contains at least one strong edge pixel is then preserved, while other BLOB"s are hidden.



(i) (ii)

Figure 2: (i) sample image , (ii) edge detected image

4. Future Scope

There are several directions for future work. We presented techniques for extracting the ear image from hair and earing, but there is currently no information on whether the system is robust when subjects wear eyeglasses.

We intend to examine whether eyeglasses can cause a shape variation in the ear and whether this will affect the algorithm. Additionally, we are interested in further quantifying the effect of pose on ICP matching results. Further study should result in guidelines that provide best practices for the use of 3D images for biometric identification in production systems. Also, speed and recognition accuracy remain important issues. We have proposed several enhancements to improve the speed of the algorithm, but the algorithm might benefit from adding feature classifiers. We have both 2D and 3D data and they are registered with each other, which should make it straightforward to test multimodal algorithms. The 2D and 3D image data sets used in this work are available to other research groups.

5. Conclusion

The system discussed advances support to the theoretical evidence that ear biometrics are a viable and promising approach to a person's identification. They are especially useful when used to supplement the existing automated methods. Though ear biometrics appear promising, additional research needs to be conducted.

Feature or appearance based: Can primitives be extracted under varying imaging conditions with sufficient reliability for a feature based approach or will appearance based approaches be necessary.

Occlusion by hair*:* In the case of the ear being completely occluded by hair there is no possibility of identification using ear biometrics, it remains to be seen with what degree of partial occlusion is identification possible and if thermo gram imagery can resolve this problem.

In conclusion we have shown that ear biometrics can be used for identification and for the further development, testing, and comparison of ear biometric algorithms the creation of an image base of ear-images and **a** set of standardized tests must be the next step.

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