International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2017 IJSRCSEIT | Volume 2 | Issue 5 | ISSN : 2456-3307

Ear Recognition using Scale Invarient Feature Transform (SIFT)

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ABSTRACT

Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. The need for biometrics can be found in federal, state and local governments, in the military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies. There exist few techniques in the literature which can be used to detect ear auto-matically. A detailed review of these techniques is as follows. The first well known technique for ear detection is due to Burge and Burger [1]. It has detected ears with the help of deformable contours. But contour initialization in this technique needs user interaction. As a result, ear localization is not fully automatic. Hurley et al. [2] have used force field technique to get the ear location. The technique claims that it does not require exact ear localization for ear recognition. However, it is only applicable when a small background is present in ear image. In [3], Yan and Bowyer have used manual technique based on two-line landmark to detect ear where one line is taken along the border between the ear and the face while other line is considered from the top of the ear to the bottom. The 2D ear localization technique proposed by Alvarez et al. [4] uses ovoid and active contour (snake) [5] models. Ear boundary is estimated by fitting the contour of an ear in the image by combining snake and ovoid models. This technique requires an initial approximated ear contour to execute and hence cannot be used in fully automated ear recognition system. There is no empirical evaluation of the technique.

Keywords : Financial Transactions, Personal Data Privacy, 2D Ear Localization Technique, Ear Detection, Difference of Gaussian

I. INTRODUCTION

Biometric-based solutions are able to provide for confidentialfinancial transactions and personal data privacy. The need for biometrics can be found in federal, state and local governments, in the military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies.

There exist few techniques in the literature which can be used to detect ear auto-matically. A detailed review of these techniques is as follows. The first well known technique for ear detection is due to Burge and Burger [1]. It has detected ears with the help of deformable contours. But contour initialization in this technique needs user interaction. As a result, ear localization is not fully automatic. Hurley et al. [2] have used force field technique to get the ear location. The technique claims that it does not require exact ear localization for ear recognition. However, it is only applicable when a small background is present in ear image. In [3], Yan and Bowyer have used manual technique based on two-line landmark to detect ear where one line is taken along the border between the ear and the face while other line is considered from the top of the ear to the bottom. The 2D ear localization technique proposed by Alvarez et al. [4] uses ovoid and active contour (snake) [5] models. Ear boundary is estimated by fitting the contour of an ear in the image by combining snake and ovoid models. This technique requires an initial approximated ear contour to execute and hence cannot be used in fully automated ear recognition system. There is no empirical evaluation of the technique. Yan and Bowyer [6] have proposed another technique by considering a predefined sector from the nose tip as the probable ear region. It first computes the ear pit using the curvature information obtained from 3D data and uses its boundary to initialize active contour which detects the ear boundary. It fails if the ear pit is occluded. It produces 78.79 % correct ear segmentation.

II. METHODS AND MATERIAL

The flow of the our work is as below

A. Phase 1: Pre-processing

In this phase, we convert the image of the ear to gray scale level according to equation 1 as follows:

$$\text{GrayImage} = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

where R is red part of the image, G is green part and B is blue part. Then we applied the median filter to enhance image and remove noise. The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is the representative of its surroundings. It replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

B. Phase 2: Ear Detection

First of all color image is converted to gray scale image. For edge detection we used canny method. The Canny method found edges by looking for local maximum of the gradient of intensity image. This method used two thresholds, to detect strong and weak edges and includes the weak edges in the output only if they are connected to strong edges [11]. This method is therefore less likely than the others to be fooled by noise, and more likely to detect true weak edges. After edge detection, connected component labeling is applied, so extra unconnected small edges are removed. We used an 8-connected neighborhood to label a pixel. From this result where maximum connected edges are found a rectangle is drawn around those edges. This rectangle shows detected ear. Then this rectangle is cropped to get the ear image isolated

C. Phase 3: Scale-Invariant Feature Detection

For any object in an image, interesting points of the object can be extracted to provide a feature description of the object. The features extracted from training images used later to identify the new object. We applied SIFT proposed by David Lowe in ICCV1999 [12] which is used to detect and describe local features in the images. We decide to use sift to extract features from ear images because it is invariant to scaling, to rotation, and to illumination. Beside that it is also robust to addition of noise.

Key-points locations are identified as local min/max of the results of Difference of Gaussian (DoG) function across scales. Then low contrast candidate points and edge response points along an edge are discarded. After that each pixel in the DoG images is compared to its eight neighbors at the same scale and nine corresponding neighboring pixels in each of the neighboring scales to obtain the DoG images. If the pixel value is the maximum or minimum among all compared pixels, it is selected as a candidate key-point.

D. Phase 4: Classification

We got key-points for each ear image and save it in the database, considering these key-points as a feature vector. When we want to test a new image we should get key-points for this image and compare it with key-points of training data. We identified this image depend on maximum match with key points in the database using minimum distance classifier.

III. RESULTS AND DISCUSSION

Following interface has been prepared in order to apply shift feature in fingerprint identification

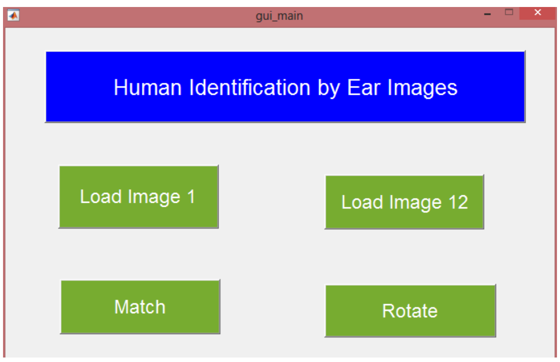
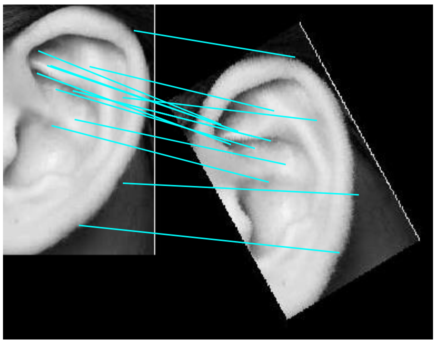
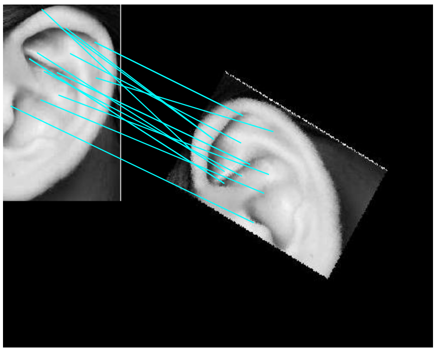


Figure1: The human ear identification system

After rotation of the image the number of key points matched have been varied as shown below



(a)



(b)

Figure 2: ear after rotational effect

The variation in the number of matching key points after the rotation is shown in the figure 3. As the angle of rotation increases, the matching points increase till angle of 30^0. After angle of 30^0 , The angle of rotation reduces.

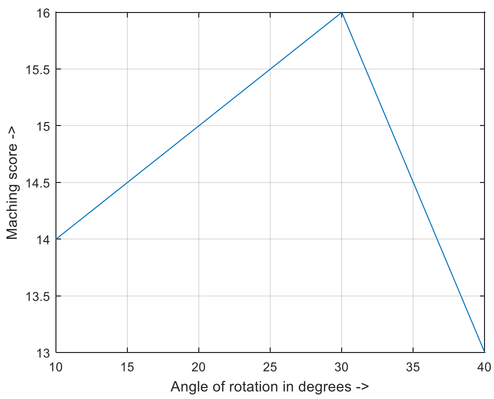


Figure 3: The effect of rotation on number of matching points

IV.CONCLUSION

From the above research work the conclusion drawn is the maximum matching keypoint found of same image with different angle. This work tries to propose methods that can reduce the effects of interferences. proposed modifications of the SIFT algorithm by introducing the Sobel operator and the EMD to reduce effect of interferences to produce more accurate matching keypoint.

According to the study the result drawn is seems to give maximum matching point that is keypoint. It can also work for small data and also gives good result for large scale.

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