Dynamic Programming-Based Ear Recognition: An Innovative Approach to Biometric Identification

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ABSTRACT

For identification and authentication of human ears we use automated ear biometrics system .Automated Ear Biometrics has recently emerged as a new area in Biometrics.The aim of this work is to evaluate the possibility of using ears for biometrics as well as devicing techniques for human identification using ears.This work can be broadly divided into three different parts.First, we find edge extraction with different filters like Laplacian of Guassian ,derivative operators, Gabor and Guassian filter.In the next part, a method for ear detection from side face image is proposed.The detection is based on detection of helix of an ear.Complete outer curve of ear is constructed from the expected helix curve.Further decisions are made on a constructed curve whether it is helix curve of ear or not.Last thing is human identification using ear. A method for human identification using ear by approximation of lines using dynamic programming.The approximated value lines thus obtained are used as features for matching ear images.

Keywords: Ear recognition; helix curve; dynamic programming;

1. INTRODUCTION

Biometrics can be described as automatically recognizing a person by certain physiological or behavioral characteristics of the person. Automating biometrics is a challenging problem in the field of Image Processing and Pattern recognition. Various physiological traits that can be used for identification of a person are face, iris, fingerprint, hand geometry. Ear biometrics has recently emerged as a new biometrics field. The number of recent researches [1, 2, 3, 4, 5, 6] show that face recognition is possible and effective for side faces by detecting and recognizing components such as ears. Hence, in this paper we present method of ear detection from 2D side face images. The rest of the paper is organized as follows.The proposed methods for ear detection and identification are described in section 2 and section 3. The experimental results are shown in section 4. Conclusion is discussed in the section 5.

2. EAR DETECTION

An algorithm for ear detection and localization based on edges of outer ear helices has been proposed. The goal of algorithm is to detect the outer helix curve of the ear. As one can observe that most common geometric shape close to ears is ellipse which is a convex shape, this property of ear shape has been used for ear detection.

The approach for ear detection from side face image can be divided into few steps. Firstly edge extraction is performed and further edge segmentation is done so that for all the curves the angle of tangent is either monotonously increasing or monotonously decreasing on moving from one end of the curve to the other end. Possible outer helix curve segment detection is done next. Complete possible outer helix curves are constructed using the curve segments and then best possible constructed curve is labeled as ear.

A block diagram for this method is shown in the figure 1

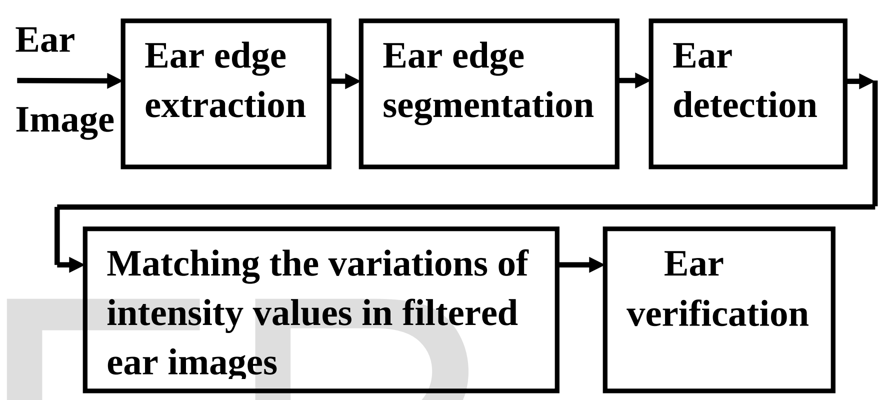

Figure 1: The block diagram of a typical ear recognition system

2.1 Edge Extraction

2.1.1 Gaussian Filter

Gaussian filter is used for smoothing or blurring a 2D image. By applying Gaussian filter, noise of the image is removed and also some information loss takes place. Gaussian filter is given by

$$g\frac{(x,y)1}{\sqrt{2\pi\sigma}}e^{\frac{\text{I-}(x\text{I}^2+y^2)}{2\sigma^2}}$$

Edge extraction is done using canny edge detector . The edges thus formed by canny edge detector are such that for a single edge some part will be belonging to ear and some part of the edge might not be belonging to the ear. Also junctions formed between edges need to be removed.

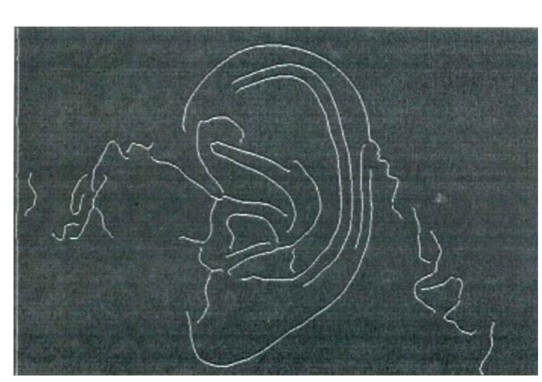

Figure 2 : Edges extracted using Canny Edge Detector

2.1.2 Removing Junction From Edges and Making Chains of Edges

The edges thus formed by canny edge detector might be containing junctions. For removing junction we perform thinning on binary image of the edges in case they are not thin. The steps for generating chain code of ear edges after removing junctions can be written as
Step 1. Perform thinning on edge image of ear formed after applying canny edge detector

Step 2. Start scanning all the pixels of the thinned image and count the number of neighborhood edge pixels to the edge pixel. If there is only one neighborhood edge pixel to the pixel, it is end point of an edge. Start a breadth first search from this pixel adding all the connected pixels to chain code.

After end of this step chain codes of edges without junctions will be obtained.

2.2 Edge Segmentation into Convex and Concave Edges

If one observes shape of ear image he can see that shape of ear curve is like an ellipse. Moreover the shape is convex. Different edges formed after edge extraction in the image are in the form of curves. Some edges will be present in the image for which some part will be belonging to ear and some will not be belonging to ear. One such edge is shown in Figure 3. There is a need to segment such edge such that the edges thus formed either belong to outer helix of ear or they don't belong to helices. Thus to segment the edges this property can be used. Break edges such that they are either convex or concave when seen from one side.

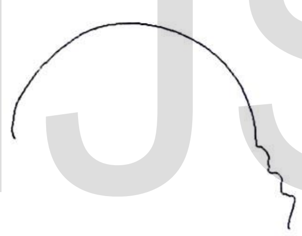

Figure 3 : The edges shown in figure is a part of outer helix curve but some part is there which does not belong to ear curve

At each point in the chain code of edge calculate the tangent angle of edge. Now if the edge is either convex or concave when seen from one side, the tangent angle will be monotonously increasing function or monotonous decreasing function. So for segmenting edges divide the edges into groups in which the angles of tangents are either monotonously increasing or monotonously decreasing. There will be regions where angles of tangent are neither increasing not decreasing i.e. those are straight lines, make those points the part of chains which are nearest to them.

2.2.1 Completing All Possible Helix Curves

After getting the possible outer helix curves, one needs to reconstruct complete outer curve of ear. Completing ear curve is done by selecting best edges that could possibly complete the curve of outer ear helix. So apply this step for all the possible helix edges found in the above mentioned step for detecting helix curves. The edge that can be added to a helix edge segment will be added such that the head of edge is joined to tail of helix edge segment or vice versa. If edge to be added is to be joined from head of the helix edge segment, let A_1 be the angle of tangent at point at the head helix curve and A_2 be angles of tangent at tail of the curve to be added and B be the angle line joining the ends. The difference of angles is calculated as,

$$D = |A_1 - B| + |A_2 - B|$$

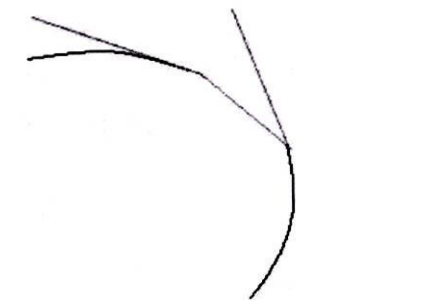

Figure 4: Lines joining ends of two curves are shown. Also the tangents at end points are shown

Let s be the distance between the end points of curves to be joined. The curve for which s*D is minimum is selected as best curve. Also only those curves are considered for which s is less than a fix threshold and D is less than a fix threshold. Also while joining the curves those curves is rejected for which line joining two ends is intersecting any other curve. Repeat the above process till the difference of angles of tangents at end points has reached a value which was experimentally determined and was found to be 230° or no further edge satisfying the above mentioned conditions is obtained. The edges thus added form the curve of outer helix.Ear detection and localization from edges is performed in this algorithm. This method does not need any template but is based on relative values of angles, so the method for detecting ear unlike most template matching based methods can detect the ears rotated in any direction in a very fast and robust manner. So for this we use ear identification by using matching the variations of intensity values in filtered ear images with the method of dynamic programming.

3.Ear Identification

3.1 Approximating Intensity Values For Faster Matching

For faster matching of the intensity values, the values are approximated by straight lines and then average of point-wise distance between approximated lines is taken as the measure of distance. This approximated distance is taken as measure for matching ears. Next two subsections explain the important concepts involved in approximate matching of the ears.

3.1.2 Method of Least Squares

Method of least squares is used to approximate a curve in the graph using best fit straight line such that the sum of error in values given by line is minimized. Formally if there are n points in the graph with coordinates given by $(1, y_1), (2, y_2), (n, y_n)$ i.e. points are of the form (i, y_i) where i is distance of the point from center and y_i is intensity value of that point and we want to approximate these points with a line $y = mx + c$ such that error is minimized.

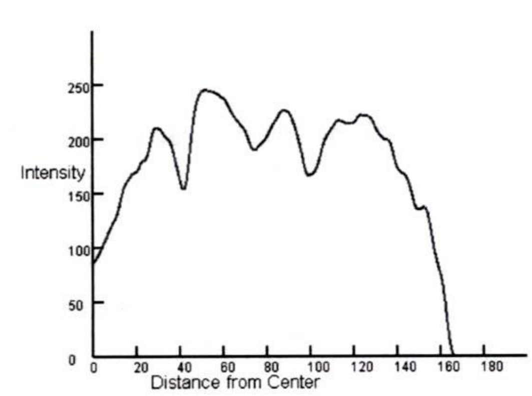

Figure 5: Intensity value vs distance from centroid graph for ear

ISSN 2229-5518

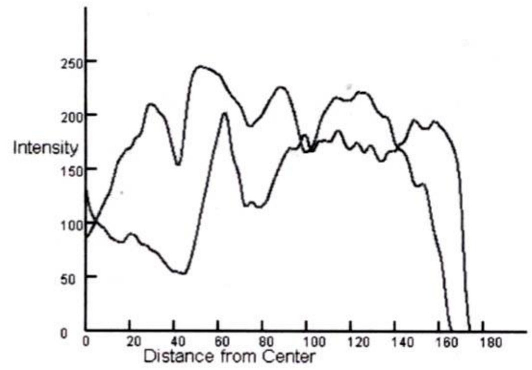

Figure 6: Intensity values vs distance for centroid graph for corresponding lines in two differ-ent ear images.

Error is given by

$$d_{final}\sum_{i=1}^{n}[y_i-(mx_i+c)]^2$$

For the best fit line with least value of error, m and c are given by

$$m=\frac{n\sum_{i=1}^{n} iy_i+\sum_{i=1}^{n} i\sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} i^2-\left(\sum_{i=1}^{n} i\right)^2}$$

$$c=\frac{\sum_{i=1}^{n} iy_i+m\sum_{i=1}^{n} i}{n}$$

Method of least square can be used for approximating Intensity vs. distance graph with a line. Intensities values shown in Figure 5 are approximated by straight lines such that average difference of approximated intensity values obtained from straight lines and actual value is at most MAXERROR.

In [7] J.G. Perez and E. Vidal have suggested dynamic programming for approximating maps using lines. In this work, dynamic programming is used for approximating the intensity values along lines. Let e[k,i,j] be the sum of errors in values when values lying in the range i to j are approximated using k lines. The steps in approximation are:

Init:

For i=1 to n

For j=i to n

Calculate e[1,i,j] using method of least squares.

While (e [k, 1, n] > n*maxerror) For i=1 to n

For j=1 to n

e[k+1,i,j] Min (e[k,i,s] + e[1,s+1,j]) where i <s < j

i.e. first the error is calculated if the graph between any point i to a point j is approximated by a single line. Next the optimal error possible on approximating graph from point i to j using k+ 1 lines is minimum error obtained on approximating a range from i to s using k lines and then rest of the values i.e. form s+ 1 to j using one line. Thus graph is approximated using p lines till the error is less than *n x maxerror*.

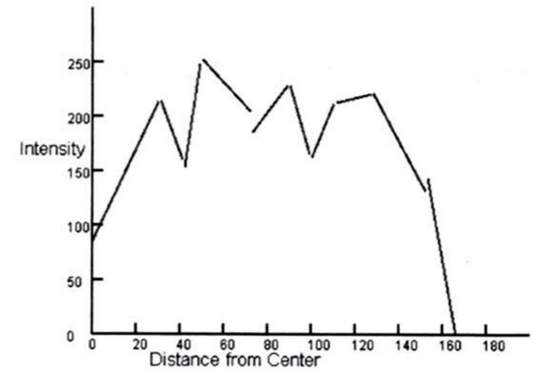

Figure 7 : Lines approximating the intensity values of graph shown in 5

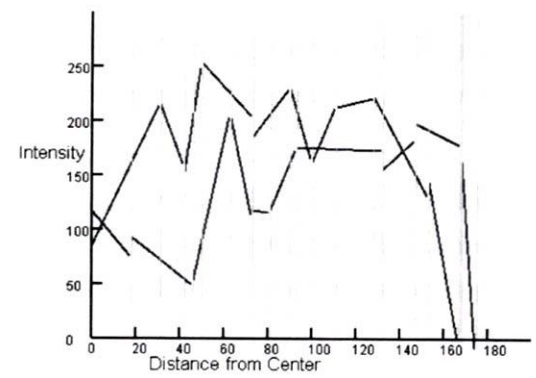

Figure 8: The graphs shown in 6 are approximated

4. EXPERIMENTAL RESULTS

The experimental setup consists of taking 3 ear images per person. A total of 300 images were taken which belonged to 100 different persons. The images were finally rotated and reduced into 256 x 512 size image with half i.e. 256 x 256 pixels belonging to ear region. 40 concurrent lines passing through centroid of ear were taken. Grey level intensity values along each line were approximated by 10 approximating lines. Rank one identification rate achieved was 97;67%. CMC curve for identification task is shown in the Figure 9.

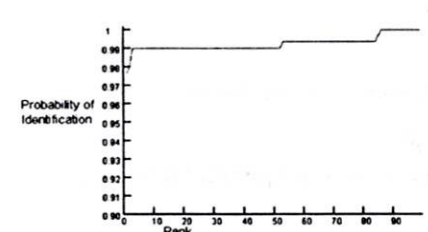

Figure 9: Cumulative match score for ear identification

The ROC curve is shown in Figure 11.

Least error of 3.23% is achieved at threshold difference of 38 in intensity values. At o 'FRR best FAR achieved was 65% and at 0 FAR best FRR achieved was 34.33%.

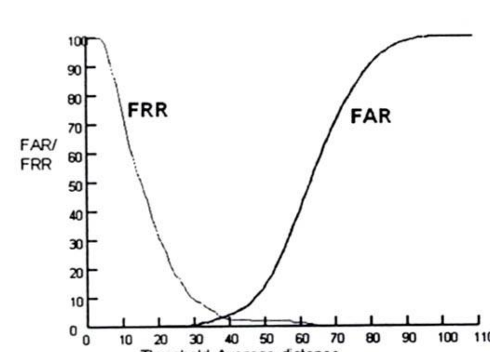

Figure 10: FAR/FRR vs threshold curve for ear recognition

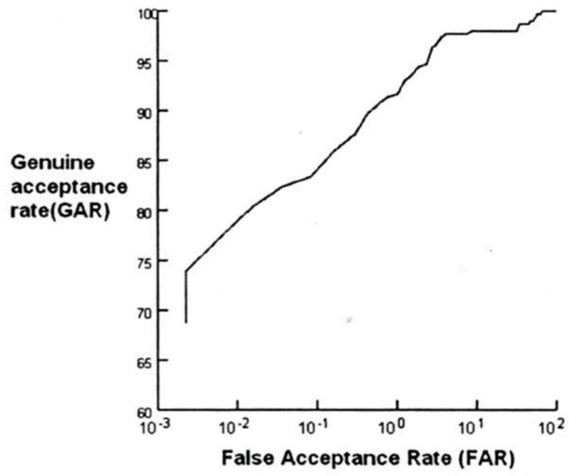

Figure 11 : ROC curve for ear recognition

5. CONCLUSION

A technique for passive human identification using ears is presented. The approach for dimensionality reduction and feature extraction from 2D ear images is simple and effective. Further the technique for human identification using ears can be improved by combining results from various other representations of ear image which are less effected from illumination changes instead of taking only gray level intensity values. Also if detection is error prone, few worst matched lines can be discarded in order to take into account the error occurred due to wrong detection of ear region.

6. REFERENCES

[1] B V Srinivasan "Ear Extraction From the Image of a HumanFace". University of Maryland, College Park.
[2] H. Chen and B. Bhanu, "Hman Ear Detection From 3D Side Face Range Images". 3D Imaging for Safety and Security,vol.35, Springer-2007, pp.133-155.
[3] S. M. S. Islam, M. Bennamoun and R. Davies, "Fast and Fully Automatic Ear Detection Using Cascaded AdaBoost" Proc. of IEEE Workshop on Application of Computer, 2008.
[4] S. Prakash, U. Jayaraman and P. Gupta, "A Skin-Color and Template Based Technique For Automatic Ear Detection". Proc. Int'l Conf. Advances in Pattern Recognition, ICAPR' 09, Feruary 2009,pp. 213-216.
[5] Sandra Maestre, Sean Nichols "DNA Biometrics", 2009
[6] R. Hietmeyer, "Biometric identification promises fast and secure processing of airline passengers," *The Int'l Civil Aviation Organization Journal*, vol. 55, no. 9, pp. 10–11, 2000
[7] J.G. Perez and E. Vidal,"Dynamic programming",2009