International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 584-589 www.ijaem.net ISSN: 2395-5252

Ears Recognition Using Filters and Least Square Method

Dr Amarendra Singh
System Manager, KNIT, Sultanpur (U. P.), India

Date of Submission: 15-12-2020 Date of Acceptance: 30-12-2020

ABSTRACT- A vast possibility for use of human ears for identification and authentication exists but· no automated ear biometrics system has been used yet. Automated Ear Biometrics has recently emerged as a new area in Biometrics. Ears can be used in multimodal biometrics after combining with face to get better results. The aim of this work is to evaluate the possibility of using ears for biometrics as well as devicing techniques for hu man identification using ears. This work can be broadly divided into three different parts. First, an evaluation study of changes in ear images due to illumination variations and changes in viewing directions is performed. The effect of changes is evaluated using different image representations including edge representation, images convolved with different filters like Laplacian of Guassian, derivative operators, Gabor and Guassian filter.

Ear biometrics can be referred as automatic measurement of distinctive ear features which can help in confirming the identity of the owner. Ear can be used for identification of a person in different forms including, taking 2D ear images of the person, by taking ear marks which are taken by pushing ears against glass. This technique is used for detecting criminals, taking 3D range images of ears. In this method the image obtained, contains 3D information and thus is very less affected by changes in illumination, shadow and surface properties. Also effect of occlusion is less in these images.

A method for human identification using ear by matching values along concurrent lines passing through center of ear image is proposed. Dimensionality reduction is done by approximating the values of 2D ear image representation along these concurrent lines. Approximation of values is done by lines using dynamic programming and method of least squares. The approximated value lines thus obtained are used as features for matching ear images.

Keywords: Filters, Laplacian of Guassian, Gabor and Guassian, Least Square Method, Helical points

I. INTRODUCTION

Biometrics can be described as automatically recognizing a person by certain physiolog ical 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. A biometrics system should be able to recognize person despite of changes in illumination condition, brightness or variations due to changes in viewing directions. Ears because of their stability, very less variability by age and easy availability [1] can be used for biometrics

Techniques used currently for personal authentication can be broadly divided into two categories, in one method a person has to carry some tokens like personal identity cards. In other method instead of carrying object person carries some information like personal identification number or password. A mix of these two ways is generally used for authentication of a person. Carrying objects has problems associating \\ith them like the person might forget to carry object with him, object getting lost and theft. A lot of cases of forging also come into picture. On the other hand passwords have problems such as forgetting, somebody using somebody else's passwords and problems of passwords getting cracked associated with them. Biometrics is the best answer to these problems. As me information contained in any biometrics characteristic is personally attached to the person to be authenticated, no such problem occurs in use of biometrics. Because of these advantages, biometrics is emerging as new tool for personal authentication.

II. WORK HAS BEEN COMPLETE TILL NOW

Various techniques for identifying a person using his ears have been proposed. Few of the major contributions are Burge and Burger's Work [5] where they have proposed an error correcting graph matching of adjacency graphs formed from generalized Voronoi diagram formed from ear edge curves. Hurley

, Nixon and Carter [6] have proposed a new method for feature extraction. Their method was based on

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 584-589 www.ijaem.net ISSN: 2395-5252

Force Field where they had considered image pixels as an array of Gaussian at tractors from which a force field is generated. Chang et al. In [7] have used Principal Component Analysis for ear biometrics. A literature survey of techniques for ear detection and recognition is provided in following subsections.

Alfred Iannarelli in [4] has proposed technique for personal identification using 12 different measurements obtained from anatomical points of ear. The measurement system is called as Iannarelli System. He had done one major study on classification of ears. He had classified around 7000 images from different ear photographs using his classification techniques. It is one of a largest study on ear which shows the feasibility of using ear as a biometrics trait.

Burge and Burger [5] have proposed error correcting graph matching technique for ear biometrics. It is first attempt for automating ear biometrics. After localizing the ear, edge extraction is done using canny edge detector. Further edge relaxation is done on larger curve segments. Smaller curve segments are removed. Generalized Voronoi diagram is made for remaining curves. Neighborhood graph is obtained from generalized voronoi diagram. Authors have proposed an novel algorithm for sub graph isomorphism which considers the possibility of broken curves. Ears are matched against each other by using their sub-graph isomorphism algorithm.

Moreno et al. In [8] have given a multiple identification method. They have used different classifiers. Among feature extraction methods. One is based on computing ear feature points heuristically, other one considers morphology of outer ear image, in one case compression network was trained. Finally various classification techniques are used like voting, Bayesian combination linear weighing and neural networks. The best identification rate of 93% is achieved using compression networks.

Hurley et al. [2, 3] have suggested a new force field transform for extracting features of ear images. The images are considered as array of mutual attractors which gives rise to Gaussian force field. Potential channels and wells were formed using force field. Convergence map of force field was used for matching ears. Force in Force field can be calculated as any of force in nature like gravitation or electrostatic force. Intensity value of pixel can be considered same as mass in case of gravitation or charge in case of electrostatics. Convergence map of force direction was taken for template matching. Convergence map was converted into binary image by segmenting it with a threshold. Further template matching was performed on segmented binary image.

Change et al. In [7] have used Principal Component Analysis for ear recognition. It is found that accuracy achieved using PCA in case of ear is worse than face. Also PCA is applied for a dataset of ear by Victor et al. In [9]. In [10J Yan and Bowyer have applied Principal Component Analysis on 2D as well as 3D ear images. They have compared the recognition rate with edge based 3D ear recognition using Hausdroff distance and found that edge based technique worked better in case of 3D ears as compared to PCA on 3D ears. Also multi modal biometrics which is a combination of 2D and 3D ear biometrics gives even better results. In [10] Yan and Bowyer have tested ear images of 300 different persons with different 2D and 3D ear recognition techniques. 2D image data is tested using. PCA (eigen-ear) and 3D data is tested using methods including Hausdroff distance of edge images obtained by extracting edges from 3D range images. PCA based recognition and rcp based recognition. PCA for range image gave worst results which are explained by holes and missing data in 3D range images. ICP on 3D ears gave best performance which is 84.1% rank one identification rate. The normalization and extraction of ear is done by using landmark points which were manually selected by the user. In [10] also, results of multi biometrics techniques using 2D and 3D ear data are given by Yan and Bowyer, which are 2D PCA, 3D PCA 3D edge based and 3D ICP based technique.

III. PROPOSED ALGORITHM USING LEAST SQUARE METHOD

For matching ears, intensity values in lines passing through centroid of grayscale histogram equalized ear image are used. For doing that, take k different concurrent lines passing through center of ear image making equal angles with each other. One of those lines is vertical i.e. along axis with minimum moment of inertia. The lines are shown in Figure 1 and graph of intensity values along a line is shown in 2. For matching ear images average of point wise distances of intensity values along corresponding lines in two different ear images is taken. Figure 1 shows 20 lines passing through center of ear region. Graph showing Intensity values vs. Distance from center values for the ear shown in Figure 1. along the axis of minimum moment of inertia is shown in Figure 2.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 584-589 www.ijaem.net ISSN: 2395-5252

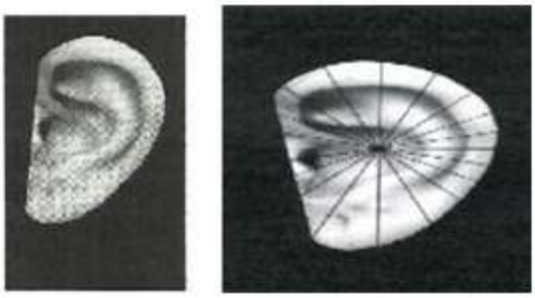

Figure 1 Original segmented image of an ear, Figure2: In the figure, 20 concurrent lines passing though center of ear are shown, intensity variation along whom is taken for matching the ears.

The average distance between two lines is calculated which in other words the area of region is between curves of two graphs divided by number of points. Let there are s points belonging to line in first ear and t points belonging to line in second Figure3 : Scaled and rotated image such that number of ear pixels is equal to number of black pixel i.e. in a 256 x 512 image 256 x 256 pixels belong to ear. Also the center of ear region is at 128,256 i.e. center of the image. Also vertical axis passing through center is the one along which ear region has least moment of inertia. Ear and will be intensity values of points along the line in first ear at distance i from center and I2i be intensity values of points along the line in second ear at distance i from center. Say s>t, average point wise distance is given by

$$d = \frac{1}{s}\sum_{i=1}^{t} |I_{1i} - I_{2i}| + \sum_{i=t+1}^{s} [I_{1i}]$$

Average distance of k such corresponding lines i.e. concurrent lines passing through centroid and making equal angles with each other is taken and final distance is given by

$$d_{final} = \frac{\sum_{i=1}^{k} d_i}{k}$$

where d_i is average distance for corresponding ith lines. The person is recognized by the ear which gives least value of d_{final} after matching against given ear.

IV. METHOD OF LEAST SQUARE

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, yi) where i is distance of the point from center and Vi is intensity value of that point and we want to approximate these points with a line y = mx + c such that error is minimized. Error is given by

Figure 3 Intensity values vs distance for centroid graph for corresponding lines in two differ-ent ear images.

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

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. But approximating a complete range with one line does not give good approximation.

V. APPROXIMATING THE INTENSITY VALUES SUCH THAT AVERAGE ERROR IS BOUNDED

Intensities values shown in Figure 4 are approximated by straight lines such that average difference of approximated intensity values obtained from straight lines and actual value is at most MAXERROR. The problem can be formally stated as, given n values of intensities i.e. n points with co-ordinates (i, y_i) for i=l to n where i is distance of the point from center and Yi is intensity value of that point. We need to approximate these values of intensities with p lines such that sum of errors in values given by approximated lines is less than n x

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 584-589 www.ijaem.net ISSN: 2395-5252

MAXERROR. Intensity values shown in Figure 4. are approximated by ten lines and corresponding approximated graph is shown in Figure 4.

In [11]' 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. After approximating values we get p lines where ith line is given b_y $y_j = m_i l + c_i$ where j $\in (r_{i-l} + 1, r_i)$.

Here m_i and C_i are m and c for ith line respectively and ri is distance of last point of ith line from center of ear.

If we don't want a dynamic number of lines for approximation rather we want a fix number of lines for approximating a set of points irrespective of value of error, only a slight modification in above algorithm will give us the desired lines. Say we need to approximate our points using MAXLINES number of lines. The code can be modified as follows.

Init:
For i=l to n For j=i to n
Calculate e[l,i,jJ using method of least squares.
For k=l to MAXLINES-l
For i=l to n For j=l to n
e[k+l,i,jJ Min (e[k,i,sJ + e[l,s+l,jJ) where i <s < j

Figure 4: Lines approximating the intensity values of graph

VI. CALCULATING DISTANCE OF APPROXIMATED LINES

Next step is to calculate the distance between approximated intensity values along corresponding lines of two ears, which will be used as matching score for ear recognition system. The end points of approximating lines form divisions for which the distances can be calculated in one step as follows. In Figure 4 various divisions are shown. The region between two vertical lines forms one division. Suppose r is the distance of first point in a division from center and there are s points in one division i.e. distance of points in the division from center is given by r, r+ 1, r+ 2 ... ... r+s-1. Also one approximating line is given by $y_{li} = m_{li} + c_l$ and other line is given by $y_{2i} = m_{2i} + c_2$ Sum of distances between points for that division is given by Distancedivision = $|y_{1i} – y_{2i}|$
= $|(m_{1i} + c_l) – (m_{2i} + c_2)|$

= $|(m_l – m_2)(rs + s(s – 1)/2) + S(c_l – c_2)$ last equality holds only when in the division

Either $y_{1i} \leq y_{2i}$ or $y_{1i} \geq y_{2i}$ fro all i.

Clearly the condition mentioned above is satisfied iff two approximating lines are not intersecting in that

division i.e. between rand r + s-1. If the lines are intersecting then the division is further broken into two parts i.e. at the point of intersection of approximating lines for satisfying the mentioned condition. Sum of distance in all the divisions is taken and further the sum is averaged to get average point-wise distance for that line. The average value of distance is calculated for all the concurrent lines in two corresponding ears. Their average gives the matching score.

VII. FORCE FIELD FEATURE EXTRACOR

Force field feature extractor was suggested by Hurley, Nixon and Carter in [5] in which potential energy channels and wells were formed. In this technique an image is considered as an array of Gaussian attractors. Potential energy calculated using this technique is similar to potential energy generated in case of gravitational or electrostatic field. Potential energy of ~ point (x,y)is given by

$$E\ (x,y) = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{I(i,j)}{\sqrt{(x-i)^2(y-j)^2}}$$

Where I (i,j) is grey level intensity value of histogram equalized grey level image. The size of image is m x n, Further

$$\vec{F}(x,y) = -\nabla(\mathbf{E}(\mathbf{x},\mathbf{y}))$$

Convergence of force direction is given by

$$C(xy,y) = -\left(\frac{\partial f_x}{\partial x} + \frac{\partial f_y}{\partial y}\right)$$

Where

$$\frac{f(x,y)(F(x,y))}{|F(x,y)|}$$

Distances were taken for potential energy values E (x,y) and for convergence map of force field, C(x,y)

VIII. RESULT AND DISCUSSION

The test was performed on 130 different ear images of 26 persons with 5 images per person described in earlier section. The evaluation was done based on hit percent of a particular filter. For each ear image distance between a person's ear image with change in illumination or viewpoint and the first image (one with left illumination without any rotation) of the same person were taken. If this distance was less than all other images of different persons belonging to the same class (same class here means the images of all the persons which had same illumination and viewing directions) the recognition was considered as a hit. The percent of hit for all the last four classes i.e. with 15° rotation, 34° rotation, same light source from right direction, a different front light source with some ambiance were calculated.

Filter	15^o change in viewpoint	34^o change in viewpoint	Light from right direction	Different front light soruce
Mean	96.15	50	0	3.84
Filter	84.61	46.15	0	12.23
Histogra	84.61	50	0	11.54
m Equalized Giassoam	84.61	50	0	7.69

σ = 2
Guassian
σ = 4

Table1: Hit percent for mean filters

Filter	15^o change in view point	34^o change in viewpoin	Light from right direction	Different front light soruce
Cos Gabor	73.07	7.69	0	50
$\theta = 0^o$ $\sigma =$	80.76	19.23	0	65.38
2λ=4	69.23	19.23	3.84	92.30
Cos Gabor	38.46	3.84	15.38	84.61

$\theta = 45^o$ $\sigma = 2\lambda$=4 Cos Gabor
$\theta = 90^o$ $\sigma = 2\lambda$=16 Cos Gabor
$\theta = 135^o$ $\sigma = 2\lambda$=12

Table 2. Delta Result

REFERENCES

[1]. Bruce E. Wampold, "Estimating Variability in Outcomes Attributable to Therapists: A Naturalistic Study of Outcomes in Managed Care. Journal of Consulting and Clinical Psychology Copyright 2005 by the American Psychological Association 2005, Vol. 73, No. 5, 914–923
[2]. D. J. Hurley1 The Ear as a Biometric, University of Southampton djh@analyticalengines.co.uk
[3]. Burge, M., and Burger, W., Ear biometrics in computer vision, Proc. ICPR 2000, pp. 822-826, 2002
[4]. Alfred Iannarelli Person Identification Using Ear Biometrics, Computer Science and Engineering Discipline, Khulna University, Khulna-9208, Bangladesh
[5]. Burge and Burger's, EAR BIOMETRICS Johannes Kepler University Linz, Austria, {burge, burger}@cast.uni-linz.ac.at}
[6]. Ibrahim, Mina Ibrahim, Nixon, Mark and Mahmoodi, Sasan (2011) Ear Detection and Recognition By Banana Wavelets. IEEE Transactions on Information Forensic and Security (Submitted)
[7]. Chang, K., Bowyer. K.W., Sarkar, S., Victor, B. Comparison and Combination of Ear and Face Images in Appearance-Based Biometrics. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 9, September 2003, pp. 1160-1165.
[8]. Moreno, B., Sánchez, Á., Vélez. J.F. On the Use of Outer Ear Images for Personal Identification in Security
[9]. Applications. IEEE 33rd Annual International Carnahan Conference on Security Technology, 1999, pp. 469-476.
[10]. Victor, B., Bowyer, K., Sarkar, S. An evaluation of face and ear biometrics in Proceedings of International Conference on Pattern Recognition, pp. 429-432, August 2002.
[11]. Yan and Bayer, A fast algorithm for ICP-based 3D shape biometrics Department of Computer Science and Engineering, University of Notre Dame, Notre Dame, IN 46556, USA
[12]. K. Messer, J. Matas, J. Kittler, J. Luettin and G. Maitre, "XM2VTSDB: The Extended M2VTS Database", Second International Conference on Audio and Videobased Biometric Person Authentication (AVBPA'99), Washington D.C., 1999, pp. 72-77