Hand Geometry as a Biometric for Human Identification

Rahul C. Bakshe¹, Dr. A. M. Patil²

¹Department of E&TC, J.T.Mahajan College of Engineering, Faizpur, Maharashtra, India ²Department of E&TC, J.T.Mahajan College of Engineering, Faizpur, Maharashtra, India

Abstract: Biometric system is widely used for identification or verification of a human based on their physical or behavioral characteristics has gained more importance in today's society where security of information is essential. Biometric systems based on hand geometry are gaining important in low to medium security applications. Hand geometry based identification systems utilize the geometric features of the hand like length and width of the fingers, diameter or perimeter of the palm also the shape of hand. The proposed system is an identification system which uses hand geometry features for user authentication. The hand shape is used which consists of only those features that cannot vary with small variation of palm position. Users can place their hands freely without the need for pegs to fix the hand placement. Most of the hand geometry systems need pegs for fixing the placement of the palm on the scanner so that hand image will capture in same pattern. The proposed system is capable to allow the user to vary the positioning of the hand on the scanner or in front of digital camera. Hence the proposed has no restriction about identification. It is capable for correct identification of human under the limited training samples.

Keywords: Biometrics, shape context, shape moment, hand geometry, kurtosis

1. Introduction

With the development of various technologies in computer field for authentication or identification of a personal has become an absolute necessary. Everything from the ATM cards to the internet requires some form of passwords for information security or for authentication. But passwords can be guessed or broken by various techniques. It is restriction for people that they should maintain difference between passwords for different applications and should change them regularly. In the modern world that would be necessary to memorize a large number of different passwords. Even access cards and identity cards can be easily stolen or it may chances of their duplicity. More and more crimes are reported everyday related to password and card theft. Biometric system for authentication is the ideal solution to all these type of requirements. It is much more user friendly than remembering a number of passwords or carrying around access cards, but most important is that it can't be stolen or cracked by any more personal.[1]

Among all the biometrics, hand geometry is one of the effective system for identification or verification of human. Hand geometry biometric system is the use of geometric shape of the hand for recognition purposes. This method was rather popular several years ago but nowadays it is seldom used. The method is based on the fact that the shape of the hand of one person differs from the shape of the hand of another person and does not change after certain age. Hand geometry as a biometric recognition can be used in Identification mode, where the system identifies a person from the entire enrolled population by searching a database of hand for a match based solely on the hand biometric.[2],[3]

In this paper we present hand geometry identification by using shape context features which is compared with shape measure by statistical functions of image processing.

2. Literature Survey

J. Fuertes et.al presents biometric identification-verification system using Support Vector Machines (SVMs) as feature extraction based on the fingers-widths and palm-print features. The combination of geometrical and palm-print data is used for feature calculation. Experiments have been performed on total 1440 samples from 144 users, 10 samples per user. Total 99.77% of recognition rate and a 0.0032% of equal error rate (EER) is reported.[4]

Aythami M. et.al proposes a novel contactless biometric system for multisampling hand recognition by including a novel acquisition device for contactless hand recognition and a study about the multi-sample acquisition as a way to improve the performance. Popular features extraction methods for hand geometry and palm print are studied and experiments have been performed on a database of 100 people with more than 2000 hand. The results suggest how a multi-sample approach outperforms the traditional single sample approach with improvements around 47% and EER of 0.21%.[5]

N. Saxena et.al presents an algorithm for recognizing the individuals using their hands automatically and a new thresholding algorithm for separating the hand from the background image consisting the lengths and widths of fingers and the width of a palm. In this method six different distance functions are tested and compared among them S1 gives the best results in both identification and verification. Matching algorithm compares and test eight different functions. In identification and verification processes, the weighted-combination of distance-IV and correlation functions yields the best performance. The identification rate is 98.72 % giving the least error. [6]

C. Lin et.al utilizes the pattern of veins in the hand biometric system. This is done by obtaining the vein pattern from the

thermal image of the palm. Heat conduction is used with several features that can be extracted from the vein patters. The false acceptance rate (FAR) up to 3.5% while the false rejection rate (FRR) upto 1.5% is obtained.[7]

AKumar et.al has presents a bimodal biometric system using fusion of shape and texture of the hand. Using discrete cosine transform palmprint authentication is done. A score level fusion of hand shape features and palmprints is done using product rule. Using either of hand shape geometry or palmprints alone produce high FRR and FAR but when the combination to form a bimodal system, it is considerably reduced. On a database of 100 users the FRR is found to be 0.6% and the FAR is found to be 0.43%.[8]

P. Rathi et.al proposed a feature extraction system using hand contour matching and obtained by using Euclidian distance from starting reference point and then tip and valley point of finger is calculated. For that data is collected by capturing six images of 50 users. Three images respectively from left and right hand is captured in three different angles (900, 1800, -1800 angles). Reduction of features and integration of new features used to improve performance. Efficiency is improved by making multimodal biometric system.[9]

3. Proposed Hand Geometry System

In this proposed system shape features are compared for identification of human using hand geometry as a biometric system. For that boundary based shape context and moment based statistical functions are calculated for identification of hand image from database. Database is a collection of hand images 25 peoples with 10 images of each person. Thus in all, we have 250 images in the self-created database. In addition with this, this algorithm is tested for Hand Geometric Points Detection Competition Database with 460 images.[10]

This proposed system is implemented using two methods such as shape context and by using shape moment feature.

3.1 Hand Geometry Identification using Shape Context Feature:

Belongie et al. introduced the idea of shape contexts and they define a descriptor for a boundary as a function of other boundary points and proposes a log-polar plot of the boundary of the shape as viewed from any arbitrary boundary value. Histogram of a log polar plot of the shape boundary is calculated to get the shape context for that particular boundary point. They reduce it to a problem of bipartite graph matching.[11]

Belongie defines shape context that are applied to images after aligning transforms. The shape descriptor computes the histograms as a feature such that they are invariant to simple transforms like scaling and translation. [12]

The first group of work, on appearance-based recognition, makes direct use of pixel brightness values [13]. This approach first attempt to find correspondences between the two images before doing the comparison. This turns out to be quite a challenge as differential optical flow techniques do not cope well with the large distortions that must be handled due to pose/illumination variations. In the recognition stage for finding correspondence will cause downstream processing errors. For building classifiers without explicitly finding correspondences there are a number of alternative methods. In such approaches, one relies on a learning algorithm having enough examples to acquire the appropriate in variances. These approaches have been used for handwritten digit recognition [11], face recognition [14], and isolated 3D object recognition [11].

Hand geometry identification using shape contexts is an approach to measuring similarity between shapes and exploits it for object recognition. We treat recognition in a nearest-neighbour classification framework as the problem of finding the stored prototype shape that is maximally similar to that in the image.

Shape contexts for hand geometry can be categorized with three main steps as follows.

- 1. Offline database building for shape contexts of all boundary points of image.
- 2. Obtain boundary points of the object and compute shape context
- 3. Shape context will be matched with the database to calculate a measure of dissimilarity.

Following Figure 3.1 shows the flow of proposed image retrieval system using shape contexts.



Figure 3.1: Flow of proposed Hand Geometry using shape context

3.1.1 Computing Cost Matrix

Consider two points p and q that have normalized K-bin histograms (i.e. shape contexts) g(k) and h(k). As shape

Volume 4 Issue 1, January 2015 <u>www.ijsr.net</u> Licensed Under Creative Commons Attribution CC BY

contexts are distributions represented as histograms, the χ^2 test statistic is used as the "shape context cost" of matching the two points:

$$C_{s} = \frac{1}{1} \sum_{K=1}^{K} \frac{[G(K) - H(K)]^{2}}{G(K) + H(K)}$$

An extra cost based on the appearance can be added in addition to the shape context cost,. For instance, it could be a measure of tangent angle dissimilarity (particularly useful in digit recognition). This is particularly useful when we are comparing shapes derived from gray-level images instead of line drawings. For example, one can add a cost based tangent orientation difference between pi and qj. The values of this range from 0 to 1.

$$C_{A} = \frac{1}{2} \left\| \begin{pmatrix} \cos(\Theta_{1}) \\ \sin(\Theta_{1}) \end{pmatrix} - \begin{pmatrix} \cos(\Theta_{2}) \\ \sin(\Theta_{2}) \end{pmatrix} \right\|$$

Now the total cost of matching the two points could be a weighted-sum of the two costs:

$$C = (1-\beta) Cs + \beta CA$$

Now for each point pi on the first shape and a point qj on the second shape, calculate the cost as described and call it Ci,j. This is the cost matrix.

3.1.2 Algorithm for Hand Geometry Identification using Shape Context Technique

- **Step 1.** The input query image is converted from RGB to binary image. Further the edges of image are detected using the preprocessing of segmentation.
- Step 2. Image is then enhance by preprocessing using Gaussian filter
- **Step 3.** Later boundary points are detected. Let B be the set of sampled boundary points. Distance(r) of each boundary point in set B from centroid point(b1)is calculated.
- **Step 4.** These calculated boundary points were be normalize by a factor λ . λ being the maximum of distance between any two points in set B.
- **Step 5.** Afterwards polar co-ordinates such as distance(r) and angle(θ) were computed for all the boundary points. The angle is computed with respect to line joining the center point b1 and the boundary point as the reference 0^0 . These features form the polar co-ordinates of the boundary point.
- **Step 6.** Log polar histograms were obtained on the shape to calculate the shape context.
- **Step 7.** Minimum distance classifier algorithm is used to match the query image with the image from database which indicates the best match
- **Step 8.** Image having best match results to the query image results is identified hand image.

3.2 Hand Geometry Identification using Shape Moment Feature

The shape of a image can also be measured by the statistics toolbox functions skewness, kurtosis, and more generally by moment. These three functions are used to give results of measure of shape in matrix with various points of the hand images.

• Kurtosis

Kurtosis is a measure of outlier-prone distribution. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; Distributions that are less outlier-prone have kurtosis less than 3. The kurtosis of a distribution is defined as

$$k = \frac{E(x-\mu)^4}{\sigma^4}$$

Where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t. Kurtosis computes a sample version of this population value.

• Central moments

Moment(X,order) returns the central sample moment of X specified by the positive integer order. Moment(x,order) will returns the central moment of the specified order for the elements of x for vector whereas moment(X, order) is used to return central moment of the specified order for each column for matrices. Moment operates along the first no singleton dimension of X for N-dimensional arrays. It could be note that the central first moment is zero while the second central moment is the variance computed using a divisor of n rather than n - 1, where n is used as length for the vector x or the number of rows in the matrix X.The central moment of order k of a distribution is defined as

$$m_k = E(x - \mu)^k$$

Where E(x) is the expected value of x.

• Skewness(X)

Skewness is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. The skewness of a distribution is defined as

$$s = \frac{E(x-\mu)^3}{\sigma^3}$$

where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t. skewness computes a sample version of this population value.

Following Figure 3.2 shows the flow of proposed hand geometry system using shape moment.

International Journal of Science and Research (IJSR) ISSN (Online): 2319-7064 Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438



Figure 3.2: Flow of proposed Hand Geometry using shape moment

3.2.1 Algorithm for Hand Geometry Identification using Shape Moment Technique

- **Step 1.** The input query image is converted from RGB to binary image. Further the edge of image is detected using the preprocessing of segmentation.
- Step 2. Image is then preprocessed to enhance by using Gaussian filter
- **Step 3.** Later boundary points are detected. Let B be the set of sampled boundary points.
- **Step 4.** Further the feature values such as skewness, kurtosis, and central moment were calculated. These values are stored as template for further matching.
- **Step 5.** Minimum distance classifier algorithm is used to match the query image with the image from database which indicates the best match
- **Step 6.** Image having best match results to the query image results is identified hand image.

4. Results and Discussions

These two algorithms were implemented for various hand image databases:

- Self-created hand images database of 25 persons with 5 images captured from each hand of all persons, in this entire database contains 250 hand images.
- Standard database of "Hand Geometric Points Detection Competition Database" with total 460 hand images.

Shape features are used for extraction of hand geometry features. Shape context and Shape moment algorithms are implemented. The performances of both the algorithm were measured in terms of accuracy. Self-created hand images were set on 1024×768 pixel size whether images in standard

database were 510×720 pixel size. Our system is capable of identifying a human from left or right hand. It can verify right hand image by using left hand image as a test image. Self-created database which has 250 images were divided as 75 images are used for testing and 175 images for training purpose. The results of implementation using shape context and shape moment in terms of accuracy is given in table 1.1

Feature Used	Accuracy in %	Time required for identification
Shape Context	92.85	263.66 sec
Shape Moment	79.01	275.65 sec

In the next experiment, we have implement both shape context and shape moment algorithm are tested for 460 standard database images which were divided as 160 test images and 350 train images.[10]

Feature Used	Accuracy in %	Time required for identification
Shape Context	96.85	209.50 sec
Shape Moment	85.71	212.40 sec

5. Conclusion

The biometric recognition system uses the physical characteristics of a person for the automatic recognition systems. The hand geometry biometric system has been proved to be more effective in various applications. The time for identification of correct hand image from testing image database with the proposed algorithm is less. We have tested out algorithm on online images of a reasonably high quality. This system can be used every time in a real-world application. The proposed system is experimented on two different algorithms in which shape context algorithm gives more accuracy than shape moment algorithm. Shape context gives 92.85% accuracy for self-created database and 96.43% accuracy for standard database.

References

- K. Jain, A. Ross, S. Prabhakar, "An Introduction to Biometric Recognition", IEEE Trans. on Circuits and Systems for Video Technology, Vol. 14, No. 1, pp 4-19, January 2004
- [2] Nicolae Duta, "A survey of biometric technology based on hand shape."Pattern Recognition 42 (2009): pp2797-2806
- [3] S Sonkamble, Dr Thool, B Sonkamble, "Survey of Biometric Recognition Systems And Their Applications", Journal of Theoretical and Applied Information Technology, pp45-51, 11,2010
- [4] J. J. Fuertes, C. M. Travieso, M. A. Ferrer, J. B. Alonso, "Intra-Modal Biometric System Using Hand-Geometry and Palmprint Texture", IEEE Transaction Paper No. ICCST-2010-16379-2, 2010.
- [5] Aythami M., Miguel A. F., Charlos M.T., Jesus B A, "Multisampling approach applied to biometrics contactless hand biometric", Security Technology (ICCST), 2012 IEEE International Carnahan Conference, pp 224 – 229 15-18 Oct. 2012,
- [6] Nidhi S., Vipul S. Neelesh D, Pragya M, "HAND GEOMETRY: A New Method for Biometric

Recognition", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-2, Issue-6, January 2013

- [7] Chih-Lung Lin and Kuo-Chin Fan. Biometric verification using thermal images of palm-dorsa vein patterns. IEEE Trans. Circuits Syst. Video Techn., 14(2):199–213.
- [8] Ajay Kumar and David Zhang. Integrating shape and texture for hand verification. In ICIG '04: Proceedings of the Third International Conference on Image and Graphics (ICIG'04), pages 222–225, Washington, DC, USA, 2004. IEEE Computer Society.
- [9] M. A. Sentosa, I K G Darma Putra, "Hand Geometry Verification based on Chain Code and Dynamic Time Warping" International Journal of Computer Applications (0975 – 8887) Volume 38– No.1, pp. 17-22 January 2012
- [10] Magalhães, F., Oliveira, H. P., Matos, H. and Campilho, A. (Published: 2010, Dez 23). HGC2011 - Hand Geometric Points Detection Competition Database [Available: http://www.fe.up.pt/~hgc2011/]. (Accessed: Feb. 2011)
- [11] Gerg Mori., S. Belongie, J. Malik, "Efficient Shape Matching Using Shape Context,," IEEE Trans. Pattern Analysis and Machine Intelligence vol. 27, no. 11, November 2005.
- [12] S. Belongie, J. Malik, and J. Puzicha, "Shape Matching and Object Recognition Using Shape Contexts," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 4, pp. 509-522, Apr. 2002.
- [13] Leibe and B. Schiele, "Analyzing Appearance and Contour Based Methods for Object Categorization," Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. 2, pp. 09-415, 2003.
- [14] Moghaddam, T. Jebara, and A. Pentland, "Bayesian Face Recognition," Pattern Recognition, vol. 33, no. 11, pp. 1771-1782, Nov. 2000