International Journal of Research in Advent Technology, Vol.6, No.7, July 2018
E-ISSN: 2321-9637
Available online at www.ijrat.org

A Survey on Biometrics of Fingerprint and Face Recognition Methods

N.V.Lalitha[1], G.Suresh[2]
Department of ECE[1,2],GMR Institute of Technology[1,2]
Email: lalitha.nv@gmrit.org[1] , suresh.g@gmrit.org[2]

Abstract-Biometric recognition systems are more famous authentication systems everywhere. This identification of the individual is based on physiological characteristics or behavioral characteristics of that person. Physiological characteristics relate to finger-print, face recognition and iris recognition, whereas behavioral characteristics deal with voice, gait and signature. This paper focus on survey of physiological biometrics viz., fingerprint and face recognition methods.

Index Terms- Biometrics, Fingerprint, Face recognition, Authentication

1. INTRODUCTION

To identify the individual on automatic basis a biometric system is used. This automatic identification is based on their physiological characteristics viz fingerprint, face, iris or behavioral characteristics viz., voice, signature, gait. Classification of biometrics system is shown in figure 1.

Fingerprints and face recognition are the most popular biometrics to identify the individual. In this paper, concentration is mainly on fingerprint and face recognition methods. The general procedure for biometric identification method is shown in figure 2. Test image may be face or fingerprint is pre-processed and then extracts the features. These features are compared with database feature set and decision takes either identified or not.

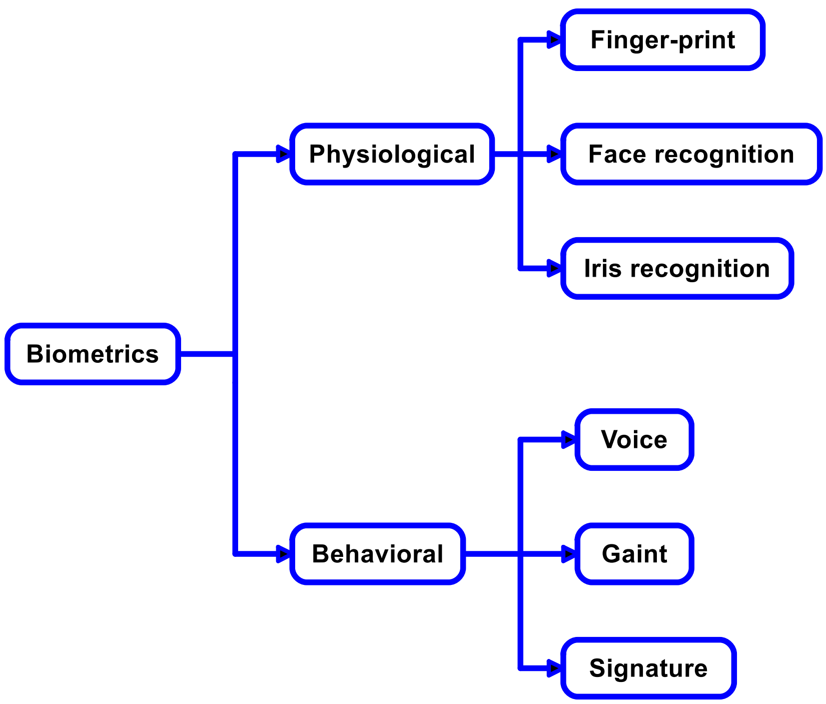

Figure 1: General classification of Biometrics

2. FINGERPRINT RECOGNITION

M B. Bhanu et al. [1] presented a fingerprint identification based on triplets of minutiae. Authors considered for triangle features are its angles, handedness, type, direction and maximum side. This method of identification is tested on entire NIST-4 database and compared with other methods for same database. This indexing approach also tested in the presence of different attacks like rotation, translation scaling ect. To avoid the use of the relative pre-alignment, F. Benhammadi et al. [2] presented a method for fingerprint matching based on minutiae texture maps. Authors reported that extracted features are invariant to rotation and translation. R. Kannavara et al. presented a method using local global graph to authenticate the corresponding fingerprint in [3]. Local graph gives the information about region magnitude, starting points, ridge bifurcation, starting, ending points etc., and global graph gives the information about relation among the different regions. This method is tested on limited database of synthetic fingerprint images. Mar Mar Min et al. [4] presented a fingerprint identification based on the features of both statistical and geometry. This method is tested on FVC-2004 database. These dataset features are calculated and stored. Unknown input fingerprint is compared with this feature set and made a decision. Conventional minutiae based fingerprint matching methods are not well matched for different fingers. Kai Cao et al. in [5] addressed this problem based on minutia handedness. In this paper, different matching rules are designed for three minutiae handedness i.e., right handed, left handed and non-handed. This method is tested on FVC2002 and FVC2004 datasets.

F. Chen et al. in [6] proposed a hierarchical minutiate matching for fingerprint and palm print identification. Here, matching method is decomposed into different stages and on each stage false fingerprints are eliminated to save time to get high identification rate. Authors reported that almost 50% time is saved compared to conventional methods. Efficiency of the many minutiate matching algorithms is poor for large fingerprint database. This problem is addressed in [7] by taking Graphics Processing Units (GPU) fingerprint matching system based on minutia cylinder code. This system keeps its accuracy and achieved speed till 100.8x compared with CPU systems. Y. Tang et al. in [8] utilized a fully convolutional network to learn features directly from data to overcome the complex background noises. In this paper, database NIST SD27 is used and achieved 53% of recall rate and precise rate. K. Cao et al. proposed a automated latent fingerprint recognition method using convolutional neural networks for ridge flow estimation and minutiae descriptor extraction. In this paper, authors work is tested on two databases i.e., NIST SD27 and WVU.

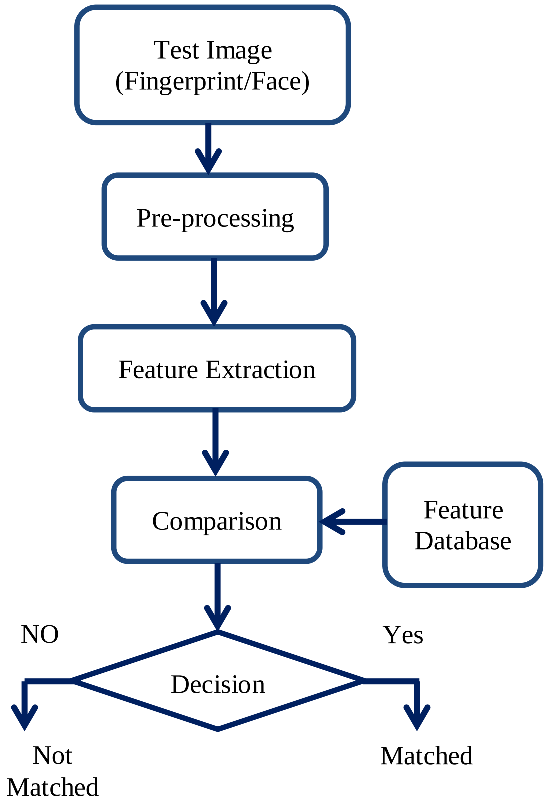

Figure 2: General procedure for biometric identification method

3. FACE RECOGNITION

Stan Z. Li et al. [9] proposed a solution for illumination invariant face recognition for indoor. In this paper, they are used active near infrared imaging system to produce face images of good quality, applied monotonic transform in the gray tone and features are generated by using local binary pattern. Here, method is compared with previous methods with respect to illumination, eyglasses, time lapse and ethnic groups. A. Albiol et al. in [10] presents a method to face recognition baed on HOG-EBGM. This work is compared with other face recognition methods and authors reported that performance of this method better than other methods for publicly available databases. B.Klare et al. examined the performance of three commercial face recognition algorithms on three demographic cohorts (gender,race/ethnicity and age) on big database of face images [11]. Authors reported that all three algorithms exhibited lower recognition accuracies on some cohorts (females, blacks and younger subjects). Authors also examined the performance of non-trainable algorithms (local binary pattern based and Gabor based) and trainable algorithms (spectrally sampled structural subspace features).

T. Barbu proposed an unsupervised automatic face recognition method based on SIFT and these features are combined with their locations [12]. One contribution of this method is that it measures the distance between generated feature vectors. Automatic region growing based clustering approach is the second contribution of this method. Author reported that, because of this automatic characteristic, this method works efficiently on large sets of human faces with higher recognition rate. J. Seo et al. presented a face recognition with partial variations using statistical learning of local features [13]. In this paper, importance of the each local feature of test images is measured by estimating the probability density of local features in training images.This method can also be applied to other types of visual recognition problems such as object recognition by choosing the appropriate training set and probability density model of local features. Y. Chu et al. proposed a cluster based regularized simultaneous discriminant analysis method [14]. Because of using cluster based scatter matrices, the problem of singularity and overfitting is resolved. This method is tested on FERET database and two complicated datasets i.e., labled faces in the wild (LFW database), real surveillance face database (Scface database).

4. CONCLUSIONS

Biometric recognition systems play a major role in authentication services. The identification can be done based on either physiological characteristics or behavioral characteristics of that person. In this paper, we reviewed the physiological biometrics viz., fingerprint and face recognition methods. This study gives a detailed summary of the methodology involved in physiological biometrics.

REFERENCES

[1] B. Bhanu and X. Tan, "Fingerprint indexing based on novel features of minutiae triplets," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 5, pp. 616–622, 2003.

[2] F. Benhammadi, M. N. Amirouche, H. Hentous, K. Bey Beghdad, and M. Aissani, "Fingerprint matching from minutiae texture maps," Pattern Recognit., vol. 40, no. 1, pp. 189–197, 2007.

[3] R. Kannavara and N. G. Bourbakis, "Fingerprint biometric authentication based on local global graphs," in IEEE 2009 National Aerospace & Electronics Conference (NAECON), 2009, pp. 200–204.

[4] M. M. Min and Y. Thein, "Intelligent fingerprint recognition system by using geometry approach," in Proceedings of the 2009 International Conference on the Current Trends in Information Technology, CTIT 2009, 2009, pp. 125–129.

[5] K. Cao et al., "Minutia handedness: A novel global feature for minutiae-based fingerprint matching," Pattern Recognit. Lett., vol. 33, no. 10, pp. 1411–1421, 2012.

[6] F. Chen, X. Huang, and J. Zhou, "Hierarchical minutiae matching for fingerprint and palmprint identification," IEEE Trans. Image Process., vol. 22, no. 12, pp. 4964–4971, 2013.

[7] P. D. Gutierrez, M. Lastra, F. Herrera, and J. M. Benitez, "A high performance fingerprint matching system for large databases based on GPU," IEEE Trans. Inf. Forensics Secur., vol. 9, no. 1, pp. 62–71, 2014.

[8] Y. Tang, F. Gao, and J. Feng, "Latent fingerprint minutia extraction using fully convolutional network," in 2017 IEEE International Joint Conference on Biometrics (IJCB), 2016, pp. 117–123.

[9] S. Z. Li, R. Chu, S. Liao, and L. Zhang, "Illumination Invariant Face Recognition Using Near-Infrared Images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 4, pp. 627–639, 2007.

[10] A. Albiol, D. Monzo, A. Martin, J. Sastre, and A. Albiol, "Face recognition using HOG-EBGM," Pattern Recognit. Lett., vol. 29, no. 10, pp. 1537–1543, 2008.

[11] B. F. Klare, M. J. Burge, J. C. Klontz, R. W. Vorder Bruegge, and A. K. Jain, "Face recognition performance: Role of demographic information," IEEE Trans. Inf. Forensics Secur., vol. 7, no. 6, pp. 1789–1801, 2012.

[12] T. Barbu, "Unsupervised SIFT-based face recognition using an automatic hierarchical agglomerative clustering solution," in Procedia Computer Science, 2013, vol. 22, pp. 385–394.

[13] J. Seo and H. Park, "Robust recognition of face with partial variations using local features and statistical learning," Neurocomputing, vol. 129, pp. 41–48, 2014.

[14] Y. Chu, T. Ahmad, G. Bebis, and L. Zhao, "Low-resolution face recognition with single sample per person," Signal Processing, vol. 141, pp. 1339–1351, 2017.