Fingerprint Recognition on Various Authentication Sensors

A. Tirupathi Rao, N. Pattabhi Ramaiah, and C. Krishna Mohan

Abstract—**Fingerprint is a very popular and an ancient biometric technology to uniquely identify a person. In this paper, a fingerprint matcher is proposed which uses the global and local adaptive binarization and global minutia features. The fingerprint data is collected using three different authentication devices based on optical sensors. The experimental results are compared with the National Institute of Standards and Technology (NIST) Bozorth algorithm and various authentication fingerprint sensors. The accuracy of the proposed algorithm has been improved significantly compared with that of the NIST Bozorth algorithm.**

Index Terms—**Authentication sensors, binarization, Bozorth algorithm, fingerprints, NIST.**

1. Introduction

A fingerprint[1] consists of ridges and valleys on the surface of the finger. The uniqueness of a fingerprint can be determined by the minutia points. Minutia points are the local ridge features which are identified by a ridge bifurcation or a ridge ending. Fingerprint matching is a difficult problem due to its large intra-class variations and small inter-class variations. Intra-class variations mean the variation of same finger among different fingerprints, whereas inter-class variations are the similarity among different fingerprints. The reason for intra-class variations are partial overlapping of fingerprints and noise formed from sensors. There are three main categories of fingerprint matching algorithms, which are correlation based, minutia based, and ridge orientation based approaches. The methods described in [2]–[7] use various filtering techniques to enhance the significant details of single fingerprint images. Fingerprint segmentation using block-wise grey-level variances or local histograms of ridge orientations were described in [8]. In [9], Gabor filters are used to divide a fingerprint into foreground and background regions. De-noising fingerprint images was presented in [10]. In this paper, we have proposed a global fingerprint matching algorithm which uses global and local adaptive binarization and global minutia features. The experiments are conducted on the fingerprint data which are captured using personal identity verification (PIV) certified authentication devices[11]. The algorithms have two different phases, one is for finding the number of matched minutia and the other phase is for validating the correctness of matching. The fingerprint data is collected using Cogent-200, BioMini-Plus, and Upek. These devices are currently under testing for the authentication applications supported by Aadhaar[11]. The data is collected from 30 subjects' 10 fingerprints in five instances.

Fig. 1 shows the images captured using the Cogent fingerprint authentication device. Fig. 2 shows the images captured using the BioMini fingerprint authentication device. Fig. 3 shows the images captured using the Upek fingerprint authentication device.

Fig. 1. Fingerprint images captured using Cogent sensor.

Fig. 2. Fingerprint images captured using BioMini sensor.

Fig. 3. Fingerprint images captured using Upek sensor.

Manuscript received May 17, 2013; revised June 26, 2013.

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Digital Object Identifier: 10.3969/j.issn.1674-862X.2014.01.026

The image dimensions for the images captured by Cogent device is 340×480, by BioMini-Plus device is 260×340, and by Upek is 256×360. All the images are captured at 500 dpi.

This paper is organized as follows. In Section 2, the overview of related work is presented. The local and global adaptive binarization technique is explained in Section 3. In Section 4, the proposed algorithm is explained. Section 5 gives the performance evaluation and results. And finally the conclusions are given in Section 6.

2. Related Work

Kaur *et al.*[13] have introduced the methods combined to create the minutia extractor and minutia matcher. Tarjoman *et al.*[14] introduced structural approach to fingerprint classification by using the directional image of fingerprints instead of singularities. Singularities detection is used to increase the accuracies. Wei *et al.*[15] proposed a method for rapid singularities searching which used the delta field Poincare index and a rapid classification algorithm to classify the fingerprint into five classes. The detection algorithm searches the direction field which changes more largely to get the singular points. Singular point detection is used to improve the accuracy. Lumini *et al.*[16] developed a method for the minutia based fingerprint and its approach to the problem as two-class pattern recognition. The obtained feature vector by minutia matching is classified into genuine or imposter by a support vector machine (SVM) resulting remarkable performance improvement. Tong *et al.*[17] proposed a method to overcome nonlinear distortion by using local relative error descriptor (LRLED). This algorithm consists of three steps: 1) A pair wise alignment method to achieve fingerprint alignment; 2) A matched minutia pair set is obtained with a threshold to reduce non-matches; 3) The LRLED based similarity measure. LRLED is good at distinguishing between the matched and non-matched minutia pairs and works well for the minutia based matching.

Jain *et al.*[18] proposed a latent fingerprint matcher based on local and global minutia matching using the similarity between latent and rolled/plain fingers. Li *et al.*[19] have proposed the extended cross matching algorithm for the fingerprint images captured from different sensor technologies namely, optical, capacitive, and thermal sensors. Some researchers proposed fingerprint identification techniques using a gray level watershed method to find out the ridges present on a fingerprint image by directly scanning the inked fingerprint impressions.

3. Local and Global Adaptive Binarization

Local and global adaptive binarization is the process that combines local mean intensity as well as global mean intensity information to binarize the fingerprint image. This combination works very well for the noisy finger prints that are captured on the fingerprint scanners, where the previous fingerprints residue is left as a ghost image on the surface of the fingerprint scanner. Global mean intensity means the sum of all the pixel intensity values divided with the total number pixels present in the image. Global binarization uses the global mean intensity as the threshold to binarize the fingerprint image, whereas the local adaptive binarization uses the mean intensity of each 8×8 block from the fingerprint image and binarizes the particular block of corresponding local mean intensity value. The proposed binarization combines both the global binarization as well as local adaptive binarization. Fig. 4 illustrates the comparison of the traditional binarization given by National Institute of Science and Technology (NIST)[12] and the proposed binarization. The proposed binarization removes the spurious minutia which is formed due to the ghost images and also improves the accuracy of fingerprint feature extraction.

Fig. 4. Images in the first column are original images, images in the second column are the NIST binarized images, and images in the third column uses the proposed binarization.

Fig. 5. Minutia (feature) extraction: left side images uses NIST binarization and right side images use the proposed binarization.

The following figure illustrates the minutia display which is implemented using the NIST binarization and the global and local adaptive binarization. The feature extraction algorithm which is used for minutia display is a NIST open source. The NIST feature extractor is little sensitive in detecting minutia and need to remove the border minutia to improve accuracy. Fig. 5 shows the minutia interpolation.

4. Proposed Fingerprint Matcher

The proposed fingerprint matching algorithm uses International Organization for Standards (ISO) fingerprint templates which are extracted by an NIST fingerprint template extractor. The following are the steps involved in the global minutia matching algorithm. The feature vector consists of the information, (x, y)-coordinates, and direction of each minutia.

- Query and reference ISO templates as input.
- Get the query and reference templates (x, y)-directions, type, and quality.
- Compute the edge pair information for each minutia to all other minutia
- Sort the edge pair information using distance.
- Compute the similarity of edge pair information in query and reference templates for similarity.
- Validate the matched minutia pairs with all other matched minutia pairs to remove false matched minutia pairs.
- Compute the matching score.

Each edge consists of the information edge distance and direction difference between minutiae at two ends. The proposed algorithm is of rotation and translation invariant.

5. Performance Evaluation and Results

The experiments are conducted on a database which is collected using three different authentication devices. The data consists of all the 10 fingerprints of 30 subjects captured at 5 different instances. The proposed algorithm improves the accuracy of the fingerprint matching. The proposed algorithm is implemented in VC++ with Intel core i3 at 2.10 MHz. We observed 500 verifications per second with the proposed algorithm on already extracted templates. Table 1 illustrates the equal error rates (EER) of Bozorth[12] and proposed fingerprint matcher algorithms on cross-sensor authentication devices.

Table 1: EER of Bozorth and proposed fingerprint matchers

Images captured using	Bozorth matcher EER	Proposed matcher EER
All three devices (cross sensed)	0.05	0.02
BioMini device	0.01	0.001
Cogent device	0.02	0.005
Upek device	0.09	0.001

The following receiver operating characteristic curves depict the results of the Bozorth and proposed fingerprint matcher algorithms using the fingerprint images captured with BioMini, Cogent, and Upek. Fig. 6 shows the results of the Bozorth and proposed algorithms using the images captured with the Biomini device. The EER with proposed algorithm is 0 and 0.01 with the Bozorth algorithm.

Fig. 7 shows the results of Bozorth and proposed algorithms using the images captured with the Cogent device. The EER with the proposed algorithm is 0.005 and with the Bozorth algorithm is 0.02. Fig. 8 shows the results of the Bozorth and proposed algorithms using the images captured with the Upek device. The EER with proposed algorithm is 0 and with the Bozorth algorithm is 0.09.

Fig. 9 shows the results of the Bozorth and proposed algorithms using the images captured with the three devices. The EER with the proposed algorithm is 0.02 and 0.05 with the Bozorth algorithm. Fig. 10 illustrates the performance of the Bozorth fingerprint matcher algorithm using four different scenarios of data. Similarly, in Fig. 11 presents the performance of the proposed fingerprint matcher algorithm using the four different scenarios of fingerprint data. We observed that the proposed algorithm gives good performance even with the fingerprint images captured using the cross-sensor fingerprint authentication devices.

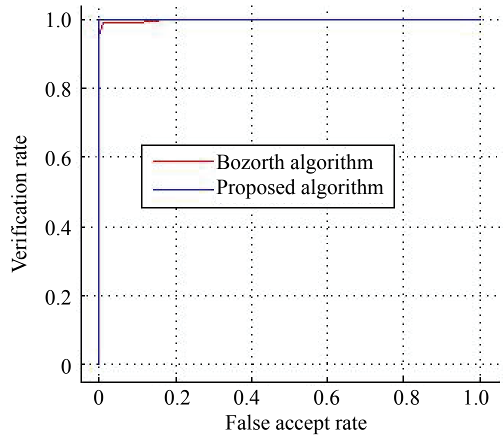


Fig. 6. Analysis on the Bozorth and proposed matcher algorithms using the images captured by the BioMini device.

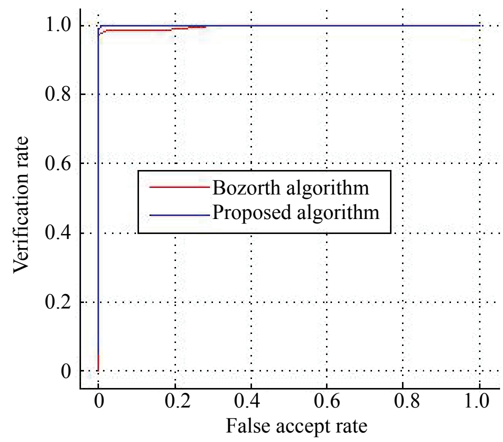


Fig. 7. Analysis on the Bozorth and proposed matcher algorithms using the images captured by the Cogent device.

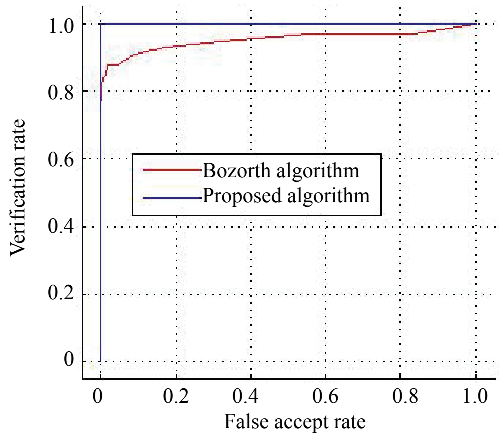


Fig. 8. Analysis on the Bozorth and proposed matcher algorithms using the images captured by the Upek device.

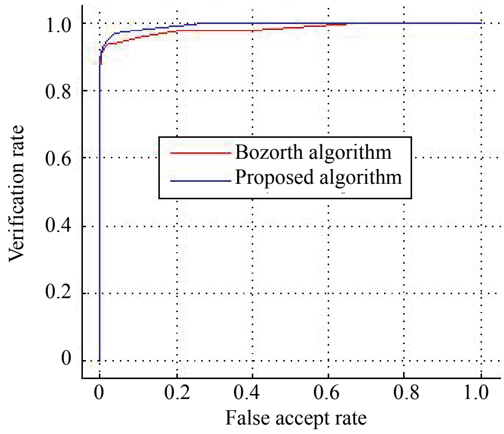


Fig. 9. Analysis on the Bozorth and proposed matchers algorithms using the images captured by all the three devices.

6. Conclusions

In this paper we have presented the local and global adaptive binarization technique and global minutia matching technique which is rotation-independent and translation-independent. The proposed algorithm uses global minutia for matching two prints. Experimental results shows that the proposed algorithm improves the EER at 0.02 whereas the existing NIST Bozorth algorithm's EER is 0.05.

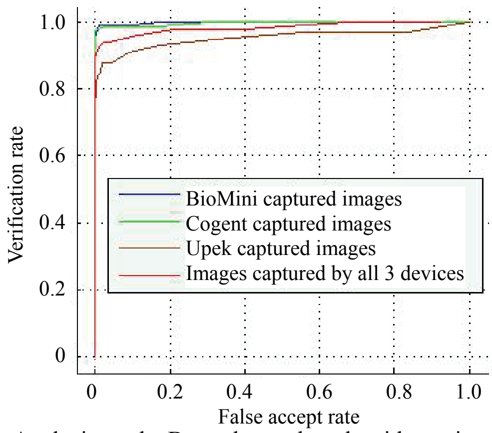


Fig. 10. Analysis on the Bozorth matcher algorithm using the images captured by all the three devices.

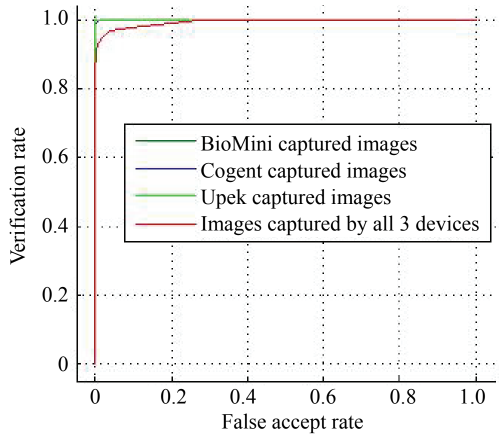


Fig. 11. Analysis on the proposed matcher algorithm using the images captured by all the three devices.

References

[1] A. Jain, U. Uludag, and A. Ross, "Biometric template selection: A case study in fingerprint domain," in *Proc. of the 4th Int. Conf. on Audio and Video-based Biometric Person Authentication*, Guildford, 2003, pp. 335–342.

[2] M. U. Arkram, S. Nasir, A. Tariq, I. Zafar, and W. S. Khan, "Improved fingerprint image segmentation using new modified gradient based technique," in *Proc. of IEEE Canadian Conf. on Electrical and Computer Engineering*, Canada, 2008, pp. 001967–001972.

[3] J.-J. Gao and M. Xie, "The layered segmentation, gabor filtering and binarization based on orientation for fingerprint preprocessing," in *Proc. of the 8th IEEE Int. Conf. on Signal Processing*, Beijing, 2006, pp. 16–20 .

[4] J.-Z. Cao and Q.-Y. Dai, "A novel online fingerprint segmentation method based on frame-difference," in *Proc. of IEEE Int. Conf. on Image Analysis and Signal Processing*, Taizhou, 2009, pp. 57–60.

[5] X.-J. Guo, G.-P. Yang, and Y.-L. Yin, "Sensor Interoperability of fingerprint segmentation: An empirical study," in *Proc. IEEE Int. Conf. on Information Engineering and Computer Science*, Wuhan, 2009, pp. 1–4.

[6] J. Qi and M. Xie, "Segmentation of fingerprint images using the gradient vector field," in *Proc. of IEEE Int. Conf. on Cybernetics and Intelligent Systems*, Chengdu, 2008, pp. 543–545.

[7] Z. Ma, M. Xie, and C.-P. Yu, "Fingerprint segmentation based on PCNN and morphology," in *Proc. of IEEE Int. Conf. on Communications, Circuits and Systems*, Milpitas, 2009, pp. 566–568.

[8] D. Maltoni, D. Maio, A. K. Jain, S. Prabhakar, *Handbook of Fingerprint Recognition*, New York: Springer, 2003.

[9] A. F. Fernando, F. A. Julian, and O. G. Javier, "An enhanced gabor filter-based segmentation algorithm for fingerprint recognition systems," in *Proc. of the 4th IEEE Int. Symposium on Image and Signal Processing and Analysis*, Zazreb, 2005, pp. 239–244.

[10] N. P. Ramaiah and C. K. Mohan, "De-noising slap fingerprint images for accurate slap fingerprint segmentation," in *Proc. of the 10th IEEE Int. Conf. on*

Machine Learning and Applications, Honolulu, 2011, pp. 208–211.

[11] M. Vatsa, R. Singh, S. Bhardwaj, and H. Bhat, “Analyzing fingerprints of Indian population using image quality: A UIDAI case study,” in *Proc. of Emerging Techniques and Challenges of Hand-Based Biometrics*, Isthanbul, 2011, pp. 1–5.

[12] A. Sankaran, M. Dhamecha, M. Vatsa, and R. Singh, “On matching latent to latent fingerprints,” in *Proc. of Int, Joint Conf, on Biometrics Compendium*, Washington, 2011, pp. 1–6.

[13] M. Kaur, M. Girdhar, and S. Sandhu, ”Fingerprint verification system using minutia extraction technique,” in *Proc. of World Academy of Science, Engineering and Technology*, vol. 36, pp. 497–502, Dec. 2008.

[14] M. Tarjoman and S. Zarei, ”Automatic fingerprint classification using graph theory,” in *Proc. of World Academy of Science, Engineering and Technology*, vol. 30, pp. 831–835, Jun. 2008.

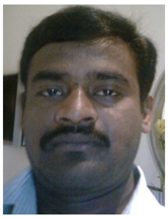
[15] W. Liu, ”Fingerprint classification using singularities detection,” *Int. Journal of Mathematics and Computer in Simulation*, no. 2, vol. 2, pp. 158–162, 2008.

[16] A. Lumini and L. Nann, ”Advanced methods for two-class pattern recognition problem formulation for minutiae-based fingerprint verification,” *The Journal of Pattern Recognition Letters*, vol. 29, pp. 286–294, Jan. 2008.

[17] X.-F. Tong, S.-B. Liu, J.-H. Huang, and X.-L. Tang, “Local relative location error descriptor-based fingerprint minutia matching,” *The Journal of the Pattern Recognition Letters*, vol. 29, pp. 286–294, Feb. 2008.

[18] A. K. Jain and J. J. Feng, “Latent fingerprint matching,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 33, no. 1, pp. 88–100, 2011.

[19] L. Li, K. Lv, and N. He, “An improved cross-matching algorithm for fingerprint images from multi-Type sensors,” in *Proc. of the 4th Int. Conf. on Image and Signal Processing*, Shanghai , 2011, pp. 1472–1475.



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