



DISTORTED FINGERPRINT MATCHING PERFORMANCE IMPROVEMENT BY ESTIMATION OF ORIENTATION MAP AND PERIOD MAP

MARY KANAKA.M

Department of ECE,

Rajas Engineering College, Raja Nagar, Vadakkangulam-627 116

Tamil Nadu, India

Mobile : +918903776875

marykanakagce@gmail.com

C.ANNA PALAGAN

Assistant Professor, Department of ECE,

Rajas Engineering College, Raja Nagar, Vadakkangulam-627

116

Tamil Nadu, India

Mobile : +919442708891

canna_palagan7467@rediffmail.com

Abstract—Elastic distortion of fingerprints is one of the major causes for false non match. Elastic distortion is introduced due to the inherent flexibility of fingertips, contact based fingerprint acquisition procedure and a lateral force or torque. While this problem affects all fingerprint recognition applications, it is especially dangerous in negative recognition applications, such as watch list and reduplication applications. In such applications, malicious users may purposely distort their fingerprints to evade identification. In this project, novel algorithms are proposed to detect and rectify skin distortion based on a single fingerprint image. Distortion detection is viewed as a two class classification problem, for which the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to perform the classification task. Distortion rectification is viewed as a regression problem, where the input is a distorted fingerprint and the output is the distortion field. To solve this problem, a database of various distorted reference fingerprints and corresponding distortion fields is built in the offline stage, and then in the online stage, the nearest neighbor of the input fingerprint is found in the reference database and the corresponding distortion field is used to transform the input fingerprint into a normal one.

Index terms: Fingerprint, distortion, nearest neighbor regression, orientation map

I. INTRODUCTION

Biometric based recognition is the science of identifying or verifying the identity of a person based on physiological and/or behavioral characteristics. Physiological traits are related to the physiology of the body and mainly include fingerprint, face, DNA, ear, iris, retina, hand and palm geometry. Behavioral traits are related to behavior of a person and examples include signature, typing rhythm, gait, voice etc. A biometric trait cannot be easily transferred, forgotten or lost, the rightful owner of the biometric template can be easily

identified, and it is difficult to duplicate a biometric trait.

A biometric system is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database. A fingerprint recognition system may operate either in verification mode or identification mode. In verification mode, the system verifies an individual's identity by comparing the input fingerprint with the individual's own template stored in the database. In the identification mode, the system identifies an individual by searching the templates of all the users in the database for a match. Elastic distortion is introduced due to the inherent flexibility of fingertips, contact based fingerprint acquisition procedure, and a purposely lateral force or torque. Skin distortion increases the intra class variations, difference among fingerprints from the same finger and thus leads to false non matches due to limited capability of existing fingerprint matchers in recognizing severely distorted fingerprints.

II. LITERATURE REVIEW

2.1 Distortion Detection Based On Special Hardware

It is desirable to automatically detect distortion during fingerprint acquisition so that severely distorted fingerprints can be rejected. Several researchers have proposed to detect improper force using specially designed hardware. However, this method has the following limitations:

- (i) They require special force sensors or fingerprint sensors with video capturing capability.
- (ii) They cannot detect distorted fingerprint images in existing fingerprint databases.
- (iii) They cannot detect fingerprints distorted before pressing on the sensor.

2.1.1 Dynamic Behavior Analysis in Compressed Fingerprint Videos: C. Dorai, N. K. Ratha, and R. M. Bolle (2004)

Dorai et al. proposed the use of fingerprint video sequences to investigate detection of two aspects of dynamic



behavior of fingerprints. Specifically, the detection of distortion of fingerprint impressions due to excessive force and the detection of positioning of fingers during image capture are addressed. These two issues often lead to difficulties in establishing a precise match between images acquired from a finger. The techniques use fingerprint video sequences to investigate dynamic characteristics of fingerprints across frames. The inter field flow estimate is used to investigate temporal characteristics of the behavior of the fingerprints. The joint temporal and motion analysis leads to reliable detection and characterization of relative finger position and pressure in streamed sequences. A significant advantage for distortion analysis is that it does not involve decompressing the video stream. The resultant biometric is efficient in terms of easy modification of compromised biometrics and is harder to produce with spoof body parts.

2.1.2 Fingerprint Image Enhancement: Algorithm And Performance Evaluation: L. Hong, Y. Wan, and A. K. Jain (1998)

L. Hong et al. proposed a fingerprint enhancement algorithm in the minutiae extraction module. They incorporated a fast fingerprint enhancement algorithm, which can adaptively improve the clarity of ridge and valley structures of input fingerprint images based on the estimated local ridge orientation and frequency, was applied. Based on the local orientation and ridge frequency around each pixel, the Gabor filter is applied to each pixel location in the image. The performance of the image enhancement algorithm was evaluated using the goodness index of the extracted minutiae and the accuracy of an online fingerprint verification system. Experimental results show that incorporating the enhancement algorithm improves both the goodness index and the verification accuracy.

2.2 Distortion Tolerant Matching

The most popular way to handle distortion is to make the fingerprint matcher tolerant to distortion. In other words, they deal with distortion on a case by case basis, i.e., for every pair of fingerprints to be compared. For the most widely used minutiae based fingerprint matching method, the following three types of strategies have been adopted to handle distortion:

- (i) Assume a global rigid transformation and use a tolerant box of fixed size or adaptive size to compensate for distortion.
- (ii) Explicitly model the spatial transformation by thin plate spline (TPS) model.
- (iii) Enforce constraint on distortion locally.

However, allowing larger distortion in matching will inevitably result in higher false match rate. In addition, allowing larger distortion in matching will also slow down the matching speed.

2.2.1 A New Algorithm For Distorted Fingerprints Matching Based On Normalized Fuzzy Similarity Measure: X. Chen, J. Tian, and X. Yang (2006)

Xinjian Chen et al. proposed a novel algorithm, normalized fuzzy similarity measure (NFSM), to deal with the nonlinear distortions. The algorithm has two main steps. First, the template and input fingerprints were aligned. In this process, the local topological structure matching was introduced to improve the robustness of global alignment. Second, the method NFSM was introduced to compute the similarity between the template and input fingerprints. Experimental results show that the algorithm gives considerably higher matching scores compared to conventional matching algorithms for deformed fingerprints. However, there are still few false acceptances in fingerprint matching process.

2.2.2 A Fingerprint Verification System Based On Triangular Matching And Dynamic Time Warping: Z. M. Kovacs Vajna (2000)

Z.M. Kovacs Vajna proposed an effective fingerprint verification system. It assumes that an existing reference fingerprint image must validate the identity of a person by means of a test fingerprint image acquired online and in real-time using minutiae matching. The matching system consists of two main blocks: the information extraction block and the matching block. The first block is used to extract the information from reference images offline. The second block is used in the matching phase online. The minutiae correspondences are found using a triangular matching algorithm and the final verification uses Dynamic Time Warping. Triangular matching is fast and overcomes the relative nonlinear deformation present in the fingerprint image pairs. In fact, triangular matching saves local regularities and compensates for global distortion. The final verification based on Dynamic Time Warping allows a very low false positive rate to be obtained.

2.3 Distortion Rectification Based On Finger Specific Statistics

Ross et al. learn the deformation pattern from a set of training images of the same finger and transform the template with the average deformation. They show this leads to higher minutiae matching accuracy. But this method has the following limitations:

- (i) Acquiring multiple images of the same finger is inconvenient in some applications and existing fingerprint databases generally contain only one image per finger.
- (ii) Even if multiple images per finger are available, it is not necessarily sufficient to cover various skin

distortions.

2.3.1 A Deformable Model For Fingerprint Matching:

A. Ross, S. C. Dass, and A. K. Jain (2005)

Ross et al. proposed an average deformation model for fingerprints based on thin plate splines (TPS). Given several template impressions of a finger, the average deformation of each template impression is estimated by comparing it with the rest of the impressions of that finger. The average deformation is developed using the thin plate spline (TPS) model and is based on minutia point correspondences between pairs of fingerprint impressions. The estimated average deformation is utilized to pre distort the minutiae points in the template image before matching it with the minutiae points in the query image. The use of an average deformation model leads to a better alignment between the template and query minutiae points. An index of deformation is proposed for choosing the deformation model with the least variability arising from a set of template impressions corresponding to a finger. Experimental results indicate that incorporating the finger specific deformation model in the matching stage improves the alignment between minutiae sets. The technique presented here uses correspondence between minutiae points of two images to compute the average deformation model. These correspondences are automatically detected and are therefore, prone to error.

2.3.2 Fingerprint Warping Using Ridge Curve Correspondences:

A. Ross, S. C. Dass, and A. K. Jain (2006)

Ross et al. proposed a deformation model for estimating the distortion effects in fingerprint impressions based on ridge curve correspondence. The performance of a fingerprint matching system is affected by the nonlinear deformation introduced in the fingerprint impression during image acquisition. This nonlinear deformation causes fingerprint features such as minutiae points and ridge curves to be distorted in a complex manner. A technique is presented to estimate the nonlinear distortion in fingerprint pairs based on ridge curve correspondences. The nonlinear distortion, represented using the thin plate spline (TPS) function, aids in the estimation of an average deformation model for a specific finger when several impressions of that finger are available. The estimated average deformation is then utilized to distort the template fingerprint prior to matching it with an input fingerprint.

2.4 Distortion Rectification Based On General Statistics

This method is based on an assumption that the ridges in a fingerprint are constantly spaced. So they deal with distortion by normalizing ridge density in the whole fingerprint into a fixed value. Since they did not have a

distortion detection algorithm, they apply the distortion rectification algorithm to every fingerprint. However, ridge density is neither fixed within a finger nor fixed across fingers. In fact, several researchers have reported improved matching accuracy due to incorporating ridge density information into minutiae matchers. Simply normalizing ridge density of all fingerprints will lose discriminating information in fingerprints and may improve impostor match scores. Furthermore, without any constraint on validity of orientation map, this method may generate fingerprints with fixed ridge period but strange orientation map. Compare to the first limitation, the second limitation is even more harmful, since it will reduce genuine match scores.

2.4.1 Detecting Fingerprint Distortion From A Single Image:

X. Si, J. Feng, and J. Zhou (2012)

Xuanbin Si et al. proposed a novel approach based on analyzing ridge period and orientation information for detecting the distorted fingerprints. Elastic distortion of friction ridge skin is one of the major challenges in fingerprint matching. Since existing fingerprint matching systems cannot match seriously distorted fingerprints, criminals may purposely distort their fingerprints to evade identification. Existing distortion detection techniques require availability of specialized hardware or fingerprint video, limiting their use in real applications. In this paper we conduct a study on fingerprint distortion and develop an algorithm to detect fingerprint distortion from a single image which is captured using traditional fingerprint sensing techniques. The detector is based on analyzing ridge period and orientation information. This algorithm still has some limitations. Firstly, the size of the distorted fingerprint database is small. Secondly, it cannot rectify distorted fingerprints such that they can be identified. This is a very important property because such unrecoverable regions do appear in some of the corrupted fingerprint images.

2.4.1 Improved Fingerprint Matching By Distortion Removal:

A. Senior, and R. Bolle (2001)

Senior and Bolle proposed a new paradigm for handling distortion in fingerprints. Fingerprint recognition is a well researched problem, and there are several highly accurate systems commercially available. However, this biometric technology still suffers from problems with the handling of bad quality prints. Recent research has begun to tackle the problems of poor quality data. Previous attempts have been made to ensure that acquired prints are not distorted, but the novel approach presented here corrects distortions in fingerprints that have already been acquired. This correction is a completely automatic and unsupervised operation. The distortion modeling and correction are explained, and results are presented demonstrating significant improvements in matching accuracy through the application of the technique.



Two models have been used. The one dimensional model appears to work well on badly distorted prints, but these are not handled well by the two dimensional model, due to lack of constraints. On only lightly distorted prints, the two dimensional model performs better.

2.4.2 Fingerprint Recognition Using Model Based Density Map: D. Wan, and J. Zhou (2006)

Jie Zhou et al. proposed a polynomial model to represent the density map and the model's parameters are saved as a novel kind of feature for the matching stage. Utilizing more information other than minutiae is much helpful for large scale fingerprint recognition applications. Thus, the density information can be utilized into the matching stage with a low additional storage cost. A decision level fusion scheme is further used to combine the density map matching with conventional minutiae based matching and experimental results showed a much better performance than using single minutiae based matching. A fingerprint matching based on modeled density map is also developed in this paper, which can be combined with conventional minutiae matching for real applications.

2.4.3 Altered Fingerprints: Analysis And Detection:

S. Yoon, J. Feng, and A. K. Jain (2012)

Anil K. Jain et al. introduced the problem of fingerprint alteration and conducted a quantitative analysis of the threat of altered fingerprints to a commercial fingerprint matcher. The widespread deployment of Automated Fingerprint Identification Systems (AFIS) in law enforcement and border control applications has heightened the need for ensuring that these systems are not compromised. While several issues related to fingerprint system security have been investigated, including the use of fake fingerprints for masquerading identity, the problem of fingerprint alteration or obfuscation has received very little attention. Fingerprint obfuscation refers to the deliberate alteration of the fingerprint pattern by an individual for the purpose of masking his identity. Fingerprint image quality assessment software e.g., NFIQ cannot always detect altered fingerprints since the implicit image quality due to alteration may not change significantly.

III. PROPOSED SYSTEM

The proposed algorithm can deal with the fingerprint distortion problem. Given an input fingerprint, distortion detection is performed first. If it is determined to be distorted, distortion rectification is performed to transform the input fingerprint into a normal one. Distortion detection is viewed as a two class classification problem, for which the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to perform the classification task. Distortion rectification or

equivalently distortion field estimation is viewed as a regression problem, where the input is a distorted fingerprint and the output is the distortion field. The final purpose of rectifying distorted fingerprints is to improve matching performance. To solve this problem, a database of various distorted reference fingerprints and corresponding distortion fields is built in the offline stage, and then in the online stage, the nearest neighbor of the input fingerprint is found in the database of distorted reference fingerprints and the corresponding distortion field is used to rectify the input fingerprint. An important property of the proposed system is that it does not require any changes to existing fingerprint sensors and fingerprint acquisition procedures. Such property is important for convenient incorporation into existing fingerprint recognition systems.

The consequence of low quality fingerprints depends on the type of the fingerprint recognition system. A fingerprint recognition system can be classified as either a positive or negative system. In a positive recognition system, such as physical access control systems, the user is supposed to be cooperative and wishes to be identified. In a negative recognition system, such as identifying persons in watch lists and detecting multiple enrollments under different names, the user of interest is supposed to be uncooperative and does not wish to be identified. In a positive recognition system, low quality will lead to false reject of legitimate users and thus bring inconvenience. The consequence of low quality for a negative recognition system, however, is much more serious, since malicious users may purposely reduce fingerprint quality to prevent fingerprint system from finding the true identity. In fact, law enforcement officials have encountered a number of cases where criminals attempted to avoid identification by damaging or surgically altering their fingerprints. Hence it is especially important for negative fingerprint recognition systems to detect low quality fingerprints and improve their quality so that the fingerprint system is not compromised by malicious users.

3.1 Fingerprint Distortion Detection

Fingerprint distortion detection can be viewed as a two class classification problem. The registered ridge orientation map and period map are used as the feature vector, which is classified by a SVM classifier. In order to extract meaningful feature vector, fingerprints have to be registered in a fixed coordinate system. For this task, a multi reference based fingerprint registration approach is proposed. A reference fingerprint is registered based on its finger center and direction. For fingerprints whose core points can be correctly detected by a Poincare index based algorithm, the upper core point is used as the finger center. For arch fingerprints and those fingerprints whose upper core points are not correctly detected, the center point is manually estimated. Finger direction is defined to be

vertical to finger joint and was manually marked for all reference fingerprints.

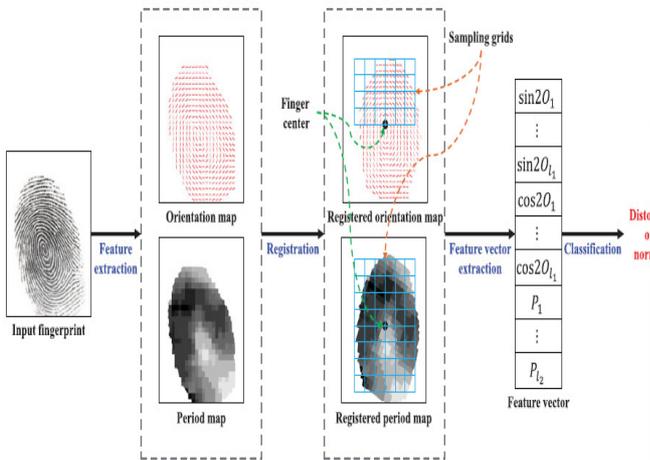


Figure 1: Flow chart of fingerprint distortion detection

A feature vector is extracted by sampling registered orientation map and period map. The sampling grid of period map covers the whole fingerprint, while the sampling grid of orientation map covers only the top part of the fingerprint. This is because the orientation maps below finger center are very diverse even within normal fingerprints. So they are not good features for distinguish distorted fingerprints from normal fingerprints. Distorted fingerprints are viewed as positive samples while normal fingerprints are viewed as negative samples. A sample is classified as a positive sample if its distortion degree computed by the proposed algorithm is above a predefined threshold.

3.2 Distorted Fingerprint Rectification

A distorted fingerprint can be thought of being generated by applying an unknown distortion field \mathbf{d} to the normal fingerprint, which is also unknown. If the distortion field \mathbf{d} is estimated from the given distorted fingerprint, it can be easily rectified into the normal fingerprint by applying the inverse of \mathbf{d} . Here, a nearest neighbor regression approach is used for this task. The proposed distorted fingerprint rectification algorithm consists of an offline stage and an online stage. In the offline stage, a database of distorted reference fingerprints is generated by transforming several normal reference fingerprints with various distortion fields sampled from the statistical model of distortion fields. In the online stage, given a distorted input fingerprint, retrieval its nearest neighbor in the distorted reference fingerprint database and then use the inverse of the corresponding distortion field to rectify the distorted fingerprint.

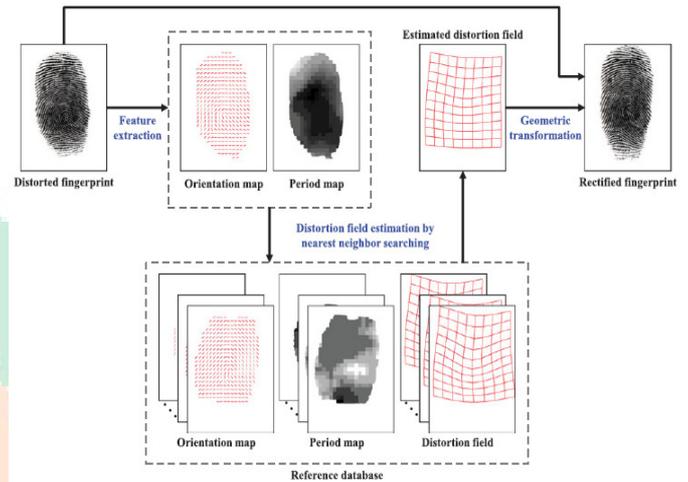


Figure 2: Flow chart of distorted fingerprint rectification

Distortion field estimation is equal to finding the nearest neighbor among all distorted reference fingerprints. The similarity is measured based on level 1 features of fingerprint, namely ridge orientation map and period map. The similarity computation method is different depending on whether the upper core point can be detected in the input fingerprint. If the upper core point is detected, the input fingerprint is translated by aligning the upper core point to center point. If no upper core point is detected, generalized Hough transform algorithm is used to compute the similarity between two fingerprints, which is more efficient for all possible translation and rotation parameters.

IV. RESULT AND DISCUSSION

Distortion detection is viewed as a two class classification problem, for which the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to perform the classification task. Distortion rectification or equivalently distortion field estimation is viewed as a regression problem, where the input is a distorted fingerprint and the output is the distortion field. To solve this problem, a database of various distorted reference fingerprints and corresponding distortion fields is built in the offline stage, and then in the online stage, the nearest neighbor of the input fingerprint is found in the database of distorted reference fingerprints and the corresponding distortion field is used to rectify the input fingerprint.

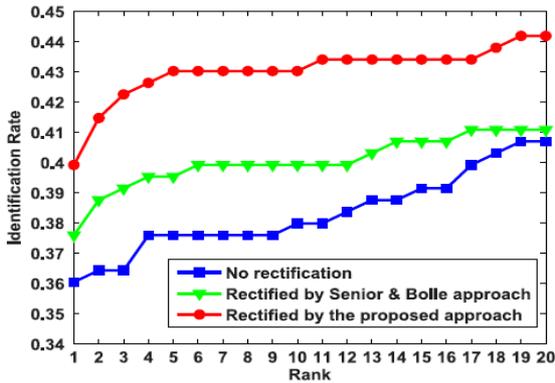


Figure 3: CMC curves of three matching experiments

An important property of the proposed system is that it does not require any changes to existing fingerprint sensors and fingerprint acquisition procedures. Such property is important for convenient incorporation into existing fingerprint recognition systems. The cumulative match characteristic (CMC) curve is commonly used to report latent matching accuracy.

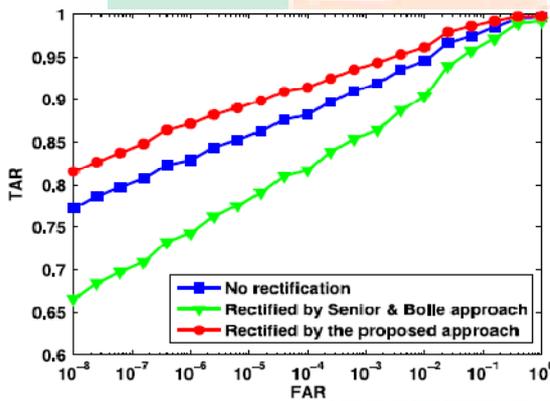


Figure 4: ROC curves of three fingerprint matching experiments

Distortion detection can be viewed as a two class classification problem. Distorted fingerprints are viewed as positive samples and normal fingerprints as negative samples. If a distorted fingerprint is classified as a positive sample, a true positive occurs. If a normal fingerprint is classified as a positive sample, a false positive occurs. By changing the decision threshold, the receiver operating characteristic (ROC) curve can be obtained.

False Rejection Rate(FRR) is the rate of occurrence of two fingerprints from same finger failing to match. FRR is the fraction of genuine fingerprints which are rejected. False Acceptance Rate(FAR) is the rate of occurrence of two fingerprints from different fingers found to match. FAR is the fraction of impostor fingerprints which are accepted.

V. CONCLUSION

False non match rates of fingerprint matchers are very high in the case of severely distorted fingerprints. This generates a security hole in automatic fingerprint recognition systems which can be utilized by criminals and terrorists. For this reason, it is necessary to develop a fingerprint distortion detection and rectification algorithms to fill the hole. This project describes a novel distorted fingerprint detection and rectification algorithm. For distortion detection, the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to classify the input fingerprint as distorted or normal. For distortion rectification, a nearest neighbor regression approach is used to predict the distortion field from the input distorted fingerprint and then the inverse of the distortion field is used to transform the distorted fingerprint into a normal one. The proposed algorithm can improve recognition rate of distorted fingerprints.

REFERENCES

- [1] C. Dorai, N. K. Ratha, and R. M. Bolle, "Dynamic behavior analysis in compressed fingerprint videos," IEEE Trans. Circuits Syst. Video Technol., vol. 14, 88no. 1, pp. 58–73, Jan. 2004.
- [2] L. Hong, Y. Wan, and A. K. Jain, "Fingerprint image enhancement: Algorithm and performance evaluation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 8, pp. 777–789, Aug. 1998.
- [3] X. Chen, J. Tian, and X. Yang, "A new algorithm for distorted fingerprints matching based on normalized fuzzy similarity measure," IEEE Trans. Image Process., vol. 15, no. 3, pp. 767–776, Mar. 2006.
- [4] Z. M. Kovacs Vajna, "A fingerprint verification system based on triangular matching and dynamic time warping," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 11, pp. 1266–1276, Nov. 2000.
- [5] A. Ross, S. C. Dass, and A. K. Jain, "A deformable model for fingerprint matching," Pattern Recognit., vol. 38, no. 1, pp. 95–103, 2005.
- [6] A. Ross, S. C. Dass, and A. K. Jain, "Fingerprint warping using ridge curve correspondences," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 1, pp. 19–30, Jan. 2006.
- [7] X. Si, J. Feng, and J. Zhou, "Detecting fingerprint distortion from a single image," in Proc. IEEE Int. Workshop Inf. Forensics Security, 2012.
- [8] A. Senior, and R. Bolle, "Improved fingerprint matching by distortion removal," IEICE Trans. Inf.



- Syst., vol. 84, no. 7, pp. 825–831, Jul. 2001.
- [9] D. Wan, and J. Zhou, “Fingerprint recognition using model based density map,” *IEEE Trans. Image Process.*, vol. 15, no. 6, pp. 1690–1696, Jun. 2006.
- [10] S. Yoon, J. Feng, and A. K. Jain, “Altered fingerprints: Analysis and detection,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 3, pp. 451–464, Mar. 2012.
- [11] A. M. Bazen, and S. H. Gerez, “Fingerprint matching by thin plate spline modeling of elastic deformations,” *Pattern Recognit.*, vol. 36, no. 8, pp. 1859–1867, Aug. 2003.
- [12] A. M. Bazen, and S. H. Gerez, “Systematic methods for the computation of the directional fields and singular points of fingerprints,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, Feb 9, 2010.
- [13] C.C. Chang, and C.J. Lin, “LIBSVM: A Library for support vector machines,” *ACM Trans. Intell. Syst. Technol.*, vol. 2, pp. 27:1–27:27, 2011.
- [14] D. H. Ballard, “Generalizing the Hough transform to detect arbitrary shapes,” *Pattern Recognit.*, vol. 13, no. 2, pp. 111–122, 1981.
- [15] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*, 2nd ed. Berlin, Germany: Springer Verlag, 2009.
- [16] D. Rueckert, A. F. Frangi, and J. A. Schnabel, “Automatic construction of 3D statistical deformation models of the brain using non rigid registration,” *IEEE Trans. Med. Imag.*, vol. 22, no. 8, 2006.
- [17] E. Tabassi, C. Wilson, and C. Watson, “Fingerprint image quality,” *Nat. Inst. Standards Technol.*, Gaithersburg, MD, USA, Tech. Rep. NISTIR 7151, Aug. 2004.
- [18] F. Alonso Fernandez, J. Fierrez Aguilar, J. Ortega Garcia, J. Gonzalez Rodriguez, H. Fronthaler, K. Kollreider, and J. Bigun, “A comparative study of fingerprint image quality estimation methods,” *IEEE Trans. Inf. Forensics Security*, vol. 2, no. 4, pp. 734–743, Dec. 2007.
- [19] F. L. Bookstein, “Principal warps: Thin plate splines and the decomposition of deformations,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 11, no. 6, pp. 567–585, Jun. 1989.
- [20] F. Turroni, R. Cappelli, and D. Maltoni, “Fingerprint enhancement using contextual iterative filtering,” in *Proc. Int. Conf. Biometrics*, 2012, pp. 152–157.
- [21] FVC2006: The fourth international fingerprint verification competition. (2006). [Online]. Available: <http://bias.csr.unibo.it/fvc2006/>
- [22] J. Dai, J. Feng, and J. Zhou, “Robust and efficient ridge based palm print matching,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 8, pp. 1618–1632, Aug. 2012.
- [23] J. Feng, “Combining minutiae descriptors for fingerprint matching,” *Pattern Recognit.*, vol. 41, no. 1, pp. 342–352, 2008.
- [24] J. Feng, J. Zhou, and A. K. Jain, “Orientation field estimation for latent fingerprint enhancement,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 4, pp. 925–940, Apr. 2013.