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Latent Fingerprint Enhancement Via Orientation Field Reconstruction And Fingerprint Alteration

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Abstract:
Fingerprints offer an infallible means of personal identification. Latents are invisible impressions of finger. Orientation field reconstruction algorithm is used to obtain an accurate estimation of fingerprint orientation field. It can improve fingerprint matching accuracy and also can enhance features from enhanced latents. A dictionary is constructed in order to get a prior knowledge of fingerprint structure. It consists of a number of orientation patches of same size. Orientation field is extracted from the fingerprint image. Orientation field describes the ridge flow of fingerprints. The initial orientation field is divided into several overlapping patches which forms the dictionary. A similarity measure is used for dictionary mapping. The similarity between an initial orientation patch and a reference orientation patch is computed by comparing corresponding orientation elements. In the proposed algorithm, reconstructed fingerprint is analyzed to determine whether it is acceptable or not. It is identified by calculating the percentage of alteration using error map and histogram. Error map calculates the absolute difference between the orientation fields. Histogram plots the number of pixels for each tonal value. The ridge orientation field analyzes the percentage of fingerprint alteration.The orientation fields of natural fingerprints vary across individuals. Therefore, the original orientation field is decomposed into two components: singular orientation field and continuous orientation field.
***Keywords*—** Latent, Orientation field, Similarity, Histogram, Error map, Dictionary, Enhancement

I. INTRODUCTION

Fingerprint is the pattern of ridges and valleys on the surface of a fingertip. A fingerprint is a type of oriented texture with locally smooth and intervening ridges and valleys. Fingerprints are claimed to be both unique and permanent, making it an ideal biometric trait for person identification. In fact, fingerprint recognition has been used by law enforcement agencies all over the world to identify suspects and victims for more than a century. Ridges are persistent throughout life except for permanent scarring. Latent fingerprints, or simply latents, have been considered as cardinal evidence for identifying and convicting criminals. The amount of information available for identification from latents is often limited due to their poor quality, unclear ridge structure and occlusion with complex background or even other latent prints.

Fingerprint enhancement is especially important to latent images; due to their poor quality orientation field estimation is a popular topic in fingerprint recognition literature. Most orientation field estimation algorithms consist of two steps: initial estimation using a gradient-based method followed by regularization. The regularization is done by a simple weighted averaging filter or more complicated model-based method [6]. To make regularization effective, it is better to use only reliable initial estimate or to give it larger weight. However, very limited information is available at this stage to estimate the reliability of initial estimate. To overcome this limitation, estimate a coarse orientation field from skeleton image generated by a commercial SDK. This coarse orientation field is further regularized by fitting an orientation field model to it.

Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image. Frequency domain processing techniques are based on modifying the Fourier transform of an image. Histograms are the basis for numerous spatial domain processing techniques. Histogram manipulation can be used effectively for image enhancement.

Image enhancement deals with improving the visual appearance of an image. Different types include noise reduction, edge enhancement and contrast enhancement. Noise reduction involves with noise i.e., random unwanted data without meaning. It removes noise from signal. Different methods used are linear smoothing filter, signal combination and anisotropic diffusion. Edge enhancement involves with edge i.e., significant local changes of intensity in an image. It contains an image processing filter that enhances the edge contrast of an image. Contrast enhancement involves with contrast i.e., difference in color that makes an object distinguishable. It improves the perceptibility of objects and enhances brightness difference between objects and their background.

Estimating orientation field of a fingerprint is a crucial stage in most fingerprint matching algorithms. Orientation field, Θ(x, y), represents the ridge flow of a fingerprint at each location. To reduce computational and storage complexity, fingerprint orientation field is generally defined at the block level rather than at the pixel level [7]. The dominant ridge orientations in a block are called orientation elements and defined in the interval [0, Π). Quality of fingerprint ridges can be improved by enhancing the local ridge clarity along the ridge orientation and suppressing noise in other directions. The purpose of an enhancement algorithm is to improve the clarity of the ridge structures and therefore make the subsequent processing, such as minutiae extraction and matching algorithm, insensitive to the quality of fingerprint images.

The paper further organized as follows: Section II proposes proposed algorithm to find the percentage of fingerprint alteration. Section III Algorithm Description while the experimental result is shown in section IV and conclusion is defined in section V.

II. PROPOSED ALGORITHM

A. Dictionary Construction

The dictionary consists of a number of orientation patches of the same size. An orientation patch consists of b x b orientation elements and an orientation element refers to the dominant orientation in a block of size 16 x 16 pixels. Construct a dictionary of orientation patches from a set of high-quality fingerprints (referred to as reference fingerprints). The orientation fields (defined on blocks of size 16 x 16 pixels) of these fingerprints are estimated using a state-of-the-art algorithm, VeriFinger 6.2 SDK [1]. High quality fingerprints and the state-of-the-art algorithm are used to ensure that the dictionary does not contain invalid words. A number of orientation patches, whose orientation elements are all available, are obtained by sliding a window (whose size is b x b blocks) across each reference orientation field and its mirrored version. Considering that the direction of the latent fingerprint is unknown, each orientation patch is rotated by 21 different angles {i.5˚,-10≤ i≤10} to generate additional orientation patches. Given these orientation patches, a greedy algorithm is employed to construct a set of reference orientation patches, which forms the dictionary.

The greedy algorithm is described below:

1. The first orientation patch is added into the dictionary, which is initially empty.
2. Then test whether the next orientation patch is sufficiently different from all the orientation patches in the dictionary. If yes, it is also added into the dictionary; otherwise, the next orientation patch is tested. Here, the similarity measure between two orientation patches of b x b blocks is computed as n_s/b^2, where ns denotes the number of orientation elements whose difference is less than 10 degrees.
3. Repeat step 2 until all orientation patches have been tested.

The number of reference orientation patches in the dictionary depends on the number of reference orientation fields and the size of the patch [8]. When the size of the patch is 10 x 10 blocks and 50 reference orientation fields are used, the number of reference orientation patches is around 23K. The size of the orientation patch has a direct impact on the ability of correcting errors in the initial orientation field. However, a large patch also requires a large dictionary, which takes more time to search.

B. Latent Fingerprint Extraction

The initial orientation field is obtained using a simple algorithm. Other local estimation algorithms, such as gradient-based and slit-based, should also suffice for this initial step. The dominant orientation in a 16x16 block is computed by detecting the peak in the magnitude spectrum of the local image [9]. Due to the poor quality of latents, the initial orientation field is usually very noisy. However, orientation field smoothing should be avoided in this stage since correct orientation elements may even be degraded by strong noise in the neighboring regions. Latent fingerprints are not visible, but techniques can “bring them out.” Dusting surfaces such as drinking glasses, the faucets on bathroom sinks, telephones, and the like with a fine carbon powder can make a fingerprint more visible. Tape is then used to lift and preserve the fingerprint.

The problem of correcting a noisy orientation field is left to the later stages, which utilize prior knowledge of fingerprints. The orientation field of a fingerprint is estimated using the following approach [10]:

- The skeleton image of the fingerprint, which is output by the VeriFinger SDK, is converted to a gray scale image using a distance transform.
- Based on the distance transform image, a block wise (8x8 pixels) binary image is created to mark foreground and background regions. A block of 8 x 8 pixels is set as

foreground if at least 80% of its pixels have values smaller than 10.

- Based on the distance transform image, a gradient-based method is used to estimate the orientation field in foreground blocks.
- Orientation values in holes of foreground (missing data) are interpolated using values on their boundary.

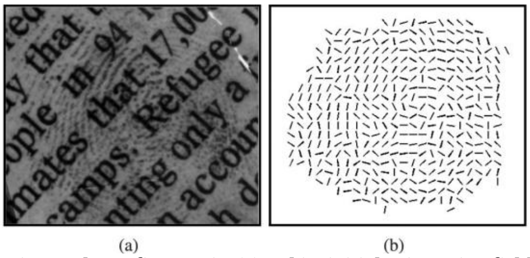

Fig 1: A latentfingerprint(a)and its initial orientation field (b)

C. Dictionary Mapping

Given an initial orientation patch that contains at least one foreground block, retrieve a list of candidate reference orientation patches from the dictionary, which are sorted according to their similarity with the initial patch. In order to retrieve the correct orientation patches at high rank, proper similarity measure and retrieval strategy need to be designed. The similarity S(Θ,Φ) between an initial orientation patch Θ and a reference orientation patch Φ[19] is computed by comparing corresponding orientation elements. Let n_f be the number of orientation elements in the initial orientation patch. Let n_s be the number of orientation elements whose differences are less than a predefined threshold (empirically set as Π=12). The similarity between two patches is defined as $S(\Theta,\Phi) = n_s/n_f$.

Orientation field correction is posed as a combinational optimization problem. The total number of possible solutions is $n_c{}^{n}{}_{p}$, where n_c is the length of candidate list and n_p is the number of patches in the input fingerprint. While a shorter list makes the search more efficient, a longer list contains the optimal solution [11]. After observing the top candidate orientation patches of many initial orientation patches, determine that the top candidates of the same initial orientation patch are quite similar to each other. However, to increase the probability of including the correct patches in a short candidate list, it is better to have a diverse set of candidates. A diverse set of n_c (empirically set as 6) candidates is selected from the top $10n_c$ initial candidates using the following greedy strategy:

1. Choose the first initial candidate.
2. The next initial candidate is compared to each of the chosen candidates. If its similarity to all the chosen candidates is below a predefined threshold (empirically set as 0.8 in our experiment), it is chosen. Similarity is measured using only the foreground blocks in the initial orientation patch[15].
3. Repeat step 2 for all the initial candidates until n_c candidates have been chosen or all initial candidates have been checked

D. Fingerprint Alteration

The percentage of fingerprint alteration is based on analyzing the ridge orientation field. Due to variations of singular points in terms of their number and location, the orientation fields of natural fingerprints also vary across individuals. Therefore, decompose the original orientation field into two components: singular orientation field and continuous orientation field [17]. The continuous orientation field (OF) of the original fingerprint is indeed continuous (i.e., no singularity), but the continuous component of the orientation field of the altered fingerprint is actually not continuous.

Extract high level features from the continuous orientation field and use a support vector machine (SVM) for classifying a fingerprint as natural fingerprint or altered one. The main steps of the proposed algorithm are described below. The orientation field of a fingerprint is estimated from the skeleton image output by the VeriFinger SDK [18].Based on the orientation field, singular points are detected following the approach. An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value.

By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance [2]. The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones. Thus, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph. Conversely, the histogram [16] for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph.

Singular orientation field is subtracted from the original orientation field to obtain its continuous component. A feature vector, called the curvature histogram, [12] is extracted from continuous orientation field using the following approach:

1) Compute difference of orientations, namely curvature, along the horizontal direction and smooth it with a Gaussian filter (σ = 2). For

natural fingerprints, the curvature curve for each image row has at most one sharp negative peak and the maximum (positive) curvature value is small.

2) Find the maximum curvature and the second minimum negative peak curvature for each image row.
3) Compute the histograms of maximum curvatures and negative peak curvatures for all image rows in 21 bins in the range [-20, 20], which are collectively termed as the curvature histogram.

The combined 42-dimensional curvature histogram [20] is input to a support vector classifier for distinguishing between natural and altered fingerprints.

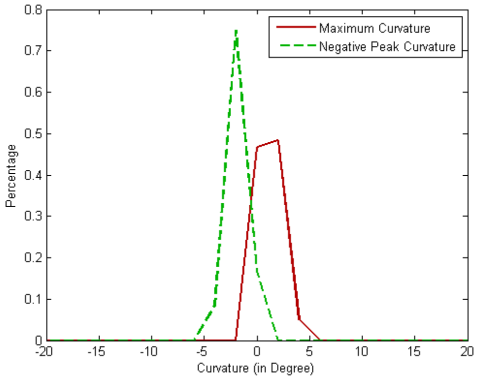

Fig: 2 Curvature histogram.

III. ALGORITHM DESCRIPTION

Detailed steps of the algorithm are as following:

Step I: Load a fingerprint image and check whether it is a color image.

Step II: Convert the gray scale image into binary image and skeletonize it.

Step III: Divide the fingerprint image into a number of non-
overlapping blocks of 16x16 pixels [14].

Step IV: Mark the variations and equivalent angle between
pixels of a block.

Step V: Draw an equivalent angle and reconstruct the image.

Step VI: Thus orientation field (variations of clear patterns) is
created.

Step VII: Orientation field is divided into a number of orientation patches of 10x 10 size.

Step VIII: Histogram plots the number of pixels for each
tonal value . Error map is computed using the
interpixel differences.

IV. EXPERIMENTAL RESULTS

Four images (original fingerprint and three types of altered fingerprints) of the first 1,000 fingerprints in SD4 are used to train LIBSVM [7]. The remaining 976 fingerprints and its altered versions are used to test the algorithm. The scores output by LIBSVM are linearly scaled to the range [0, 1]. The normalized score is termed as fingerprint-ness. When the fingerprint-ness of an input image is smaller than a predetermined threshold, system raises an alarm for altered fingerprints. If this image is indeed an altered fingerprint, it is a true detection; otherwise it is a false alarm.

To construct a dictionary of reference orientation patches, a set of good quality fingerprints in the NIST SD4 database is used. All five major pattern types (plain arch, tented arch, left loop, right loop and whorl) are covered by these 50 fingerprints [3].

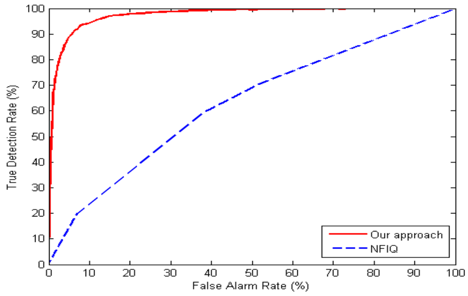

Fig 3. ROC curves of NFIQ and our approach.

The distributions of NFIQ values and fingerprintness of original and altered fingerprints. The proposed algorithm can separate original fingerprints from altered fingerprints much better than NFIQ. As shown in the ROC curves in Fig. 3, at a false alarm rate of 7% (NFIQ value of 4, our threshold value of 0.58), 92% of the altered fingerprints were detected using our approach, but only 20% of them were detected by NFIQ. The proposed algorithm was tested using altered fingerprints synthesized in ways typically observed in operational cases and a small number of available real altered fingerprints. Combining orientation field and scar information further improve the detection rate of altered fingerprints.

V. CONCLUSION

In summary, it has been concluded that the proposed technique is giving much better results than the existing ones. In fingerprint image processing, a good and reliable orientation field reconstruction is a crucial preprocessing step, because many subsequently applied methods for image enhancement, binarization, and feature extraction require information about the local ridge orientation, and computing singular points using the Poincare index is based on the orientation field.

A dictionary consists of a number of orientation patches of same size. Orientation field describes the ridge flow of fingerprints. The initial orientation field is divided into several overlapping patches which forms the dictionary.[4] A similarity measure is used for dictionary mapping. The similarity between an initial orientation patch and a reference orientation patch is computed by comparing corresponding orientation elements.

In the proposed algorithm, reconstructed fingerprint is analyzed to determine whether it is acceptable or not. It is identified by calculating the percentage of alteration using error map and histogram [13]. Error map calculates the absolute difference between the orientation fields. Histogram plots the number of pixels for each tonal value. The proposed algorithm based on the features extracted from the orientation field and minutiae satisfies the three essential requirements for alteration detection algorithm: fast operational time, high true positive rate at low false positive rate, and ease of integration into AFIS [5]. This study can be further extended along the following directions:

1. Determine the alteration type automatically so that appropriate countermeasures can be taken.
2. Reconstruct altered fingerprints. For some types of altered fingerprints where the ridge patterns are damaged locally or the ridge structure is still present on the finger but possibly at a different location, reconstruction is indeed possible.
3. Match altered fingerprints to their unaltered mates. A matcher specialized for altered fingerprints can be developed to link them to unaltered mates in the database utilizing whatever information is available in the altered fingerprints.

REFERENCES

[1] A.K.Jain, J.Zhou and J. Feng, “Orientation Field Estimation For Latent Fingerprint Enhancement,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 35, no. 4, pp. April. 2013.

[2] J. Feng, S. Yoon, and A.K. Jain, “Altered Fingerprints: Analysis and Detection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 34, no. 3, pp. 451-464, 2012.

[3] R. Rama and A.M. Namboodiri, “Fingerprint Enhancement Using Hierarchical Markov Random Fields,” Proc. Int’l Joint Conf. Biometrics, 2011

[4] R. Cappelli, A. Lumini, D. Maio, and D. Maltoni, “Fingerprint Image Reconstruction from Standard Templates,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol.9, no. 9, pp. 1489-1503, Sept. 2007

[5] B.T. Ulery, R.A. Hicklin, J. Buscaglia, and M.A. Roberts,“Repeatability and Reproducibility of Decisions by Latent Fingerprint Examiners,” PLUS ONE, vol. 7, no.3, p. e32800, 2012.

[6] L. Fan, S. Wang, H. Wang, and T. Guo, “Singular Points Detection Based on Zero-Pole Model in Fingerprint Images,” IEEE Trans. Pattern Analysis and Machine Intelligence,vol. 30, no. 6, pp. 929-940, June 2008.

[7] C. Gottschlich, P. Mihailescu, and A. Munk, “Robust Orientation Field Estimation and Extrapolation Using Semi local Line Sensors,” IEEE Trans. Information Forensics and Security, vol. 4, no. 4,pp. 802-811, Dec. 2009.

[8] B.G. Sherlock and D.M. Monro, “A Model for Interpreting Fingerprint Topology,”Pattern Recognition, vol. 26, no. 7, pp. 1047-1055, 1993.

[9] S. Yoon, J. Feng, and A.K. Jain, “Latent Fingerprint Enhancement via Robust Orientation Field Estimation,” Proc. Int’l Joint Conf. Biometrics, 2011.

[10] A.K. Jain and J. Feng, “Latent Palmprint Matching,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 31, no. 6, pp. 1032- 1047, June 2009.

[11] S.C. Dass, “Markov Random Field Models for Directional Field and Singularity Extraction in Fingerprint Images,” IEEE Trans.Image Processing, vol. 13, no. 10,pp. 1358-1367, Oct. 2004.

[12] X. Jiang, “Extracting Image Orientation Feature by Using Integration Operator,” Pattern Recognition, vol. 40, no. 2, pp. 705-717, 2007.

[13] K.-C. Lee and S. Prabhakar, “Probabilistic Orientation Field Estimation for Fingerprint Enhancement and Verification,” Proc.Biometrics Symp., pp. 41-46,Sept. 2008.

[14] F. Chen, J. Feng, A.K. Jain, J. Zhou, and J. Zhang, “Separating Overlapped Fingerprints,” IEEE Trans. Information Forensics and Security, vol. 6, no. 2, pp. 346-359, June 2011.

[15] M. Kass and A. Witkin, “Analyzing Oriented Patterns,” Computer Vision, Graphics, and Image Processing, vol. 37, no. 3, pp. 362-385,1987.

[16] J. Li, W.-Y. Yau, and H. Wang, “Constrained Nonlinear Models of Fingerprint Orientations with Prediction,” Pattern Recognition, vol. 39, no. 1, pp. 102-114, 2006.

[17] E. Zhu, J. Yin, C. Hu, and G. Zhang, "A Systematic Method for Fingerprint Ridge Orientation Estimation and Image Segmentation," Pattern Recognition, vol. 39, no. 8, pp. 1452-1472, 2006.

[18] M.A. Oliveira and N.J. Leite, "A Multiscale Directional Operator and Morphological Tools for Reconnecting Broken Ridges in Fingerprint Images," Pattern Recognition, vol. 41, no. 1, pp. 367-377, 2008.

[19] J. Gu, J. Zhou, and C. Yang, "Fingerprint Recognition by Combining Global Structure and Local Cues," IEEE Trans. Image Processing, vol. 15, no. 7, pp. 1952-1964, July 2006.

[20] M. Kass and A. Witkin, "Analyzing Oriented Patterns," Computer Vision, Graphics, and Image Processing, vol. 37, no. 3, pp. 362-385, 1987.

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