Identify and Rectify the Distorted Fingerprints

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Abstract:- Elastic distortion of fingerprints is the major causes for false non-match. While this cause disturbs all fingerprint recognition applications, it is especiallyrisk in negative recognition applications, such as watch list and deduplication applications. In such applications, malicious persons may consciously distort their fingerprints to hide identification. In this paper, we suggested novel algorithms to detect and rectify skin distortion based on a single fingerprint image. Distortion detection is displayed as a two-class categorization problem, for which the registered ridge orientation map and period map of a fingerprint are beneficial as the feature vector and a SVM classifier is trained to act the classification task. Distortion rectification (or equivalently distortion field estimation) is viewed as a regression complication, where the input is a distorted fingerprint and the output is the distortion field. To clarify this problem, a database (called reference database) of various distorted reference fingerprints and corresponding distortion fields is built in the offline stage, and then in the online stage, the closest neighbor of the input fingerprint is organized in the reference database and the corresponding distortion field is used to transform (Convert) the input fingerprint into a normal fingerprints. Promising results have been obtained on three databases having many distorted fingerprints, namely FVC2004 DB1, Tsinghua Distorted Fingerprint database, and the NIST SD27 latent fingerprint database.

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1. Introduction

Although automatic fingerprint recognition technologies have briskly advanced during the last forty years, there still exists many challenging research problems, for example, recognizing low quality fingerprints[2]. Finger-print matcher is very sensitive to image quality as seen in the FVC2006, where the matching accuracy of the same algorithm varies significantly among different data-sets due to variation in image quality. The variation between the accuracies of plain, rolled and latent fingerprint matching is even larger as found in technology evaluations conducted by the NIST.

The consequence of low quality fingerprints depends on the type of the fingerprint recognition system. A fingerprint recognition system can be categorized as either a positive or negative system. In a positive recognition system, such as physical access control systems, the end-user is supposed to be cooperative recognition and wishes to be identified. In a negative system, such as identifying persons in watch lists and detecting multiple enrollments under different names, the user of concern (e.g., criminals) is supposed to be uncooperative and does not want to be identified. In a positive recognition system, low quality will points to false reject of legitimate persons and thus bring inconvenience. The effect of low quality for a negative recognition system,

However, is 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 small quality fingerprints and increase their quality so that the fingerprint system is not compromised by malicious persons. Degradation of finger-print quality can be photometric or geometrical. Photometric degradation can be effected by non-ideal skin conditions, dirty sensor surface, and complex image background (in latent fingerprints). Geometrical degradation is mainly caused by skin distortion. On the contrary, geometrical degradation due to skin distortion has not yet received sufficient attention, despite of the importance of this problem. This is the problem this paper attempts to address. Note that, for a negative fingerprint recognition system, its security level is as low as the lowest point. Thus it is urgent to develop distorted fingerprint (DF) detection and rectification algorithms to fill the hole. Elastic distortion is introduced due to the inherent flexibility of fingertips, contact-based fingerprint acquisition procedure, and a purposely lateral force or torque, etc. Skin distortion increased the intra-class variations (difference among fingerprints from the same finger) and thus leads to false unmatched due to limited capability of existing fingerprint matchers in recognizing severely distorted finger-prints.

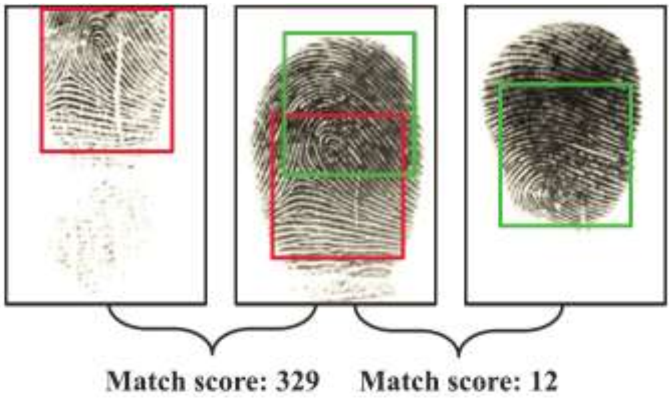

Fig. 1.Three impressions of the same finger. The left two are normal fingerprints, while the right one contains severe distortion. The match score in-between the left two according to VeriFinger 6.2 SDK is much higher than the match score in-between the right two. This large difference is due to distortion rather than overlapping area. As displayed by red and green rectangles, the overlapping area is same in two cases.

In Fig. 1, the left two are normal fingerprints, while right figure contains maximum distortion. According to Veri-Finger 6.2 SDK, the match score in-between the left two is much higher than the match score between the right two. This large difference is due to distortion rather than over-lapping area. While it is possible to make the matching algorithms tolerate huge skin distortion, this will lead to more false matches and slow down matching speed. The Fig.2 for the flowchart of the proposed system. Providing an input finger-print, distortion detection of fingerprint is performed first. If it is determined to be distorted, distortion rectification is performed to convert theprovided input fingerprint into normal fingerprints. A distorted fingerprint is analogous to a face with expression, which alter the matching efficiency of face recognition systems. Rectifying a distorted fingerprint into a normal fingerprint is analogous to converting a face with expression into a neutral face, which can improve face recognition performance.

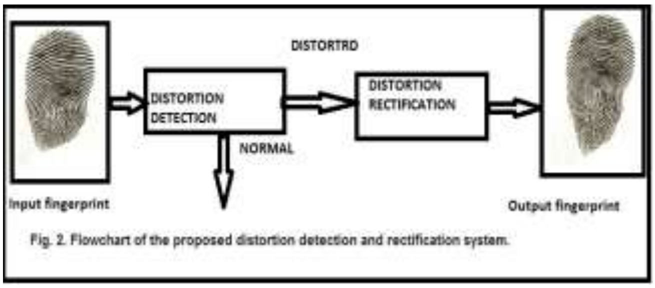

Fig. 2. Flowchart of the proposed distortion detection and rectification system.

2. Related Work:

Due to the major importance of recognizing distorted fingerprints,the various proposed method can be classified into four categories

2.1 Distortion-Tolerant Matching:

The most suitable way to handle distortion is to make the matcher tolerant to distortion. [8]– [10].In another words, they deal with distortion for each pair of fingerprints to be compared. For example, the following three types of strategies to handle distortion: (i) Assume a global rigid transformation and use a tolerant box of fixed size to compensate for distortion[8]; (ii) explicitly model the spatial transformation [9] by Thin-Plate Spline model; and (iii) only enforce constraint on distortion locally [10]. However, allowing huge distortion in matching will inevitably outcomes in higher false match rate. For example, if we enhanced the bounding zone around a minutia, many nonmatched minutiae will have a chance to get paired.

2.2 Fingerprint Adjustment

Senior and Bolleconcern with distortion by normalizing ridge density in the whole fingerprint to a fixed value [11]. They showed this can boost genuine match scores. However, ridge density is known to contain discriminating information and numbers of researchers have reported to boost matching accuracy due to incorporating ridge density [12], [13] in information into minutiae matchers. Simply unifying ridge density of all fingerprints will lose discriminating information in fingerprints and may increase false match rate. Ross et al learn the deformation pattern from a set of training images of the same finger and transform the template with the least deformation using the moderate deformation with other images. They show this leads to larger than minutiae matching accuracy. But this method has the following constrains: (i) acquiring multiple images of the same finger is inconvenient in some applications and existing fingerprint databases generally contain only one image per finger; and (ii) even if multiple images per finger are available, a malicious user can still adopt unusual distortion, which is not reflected in the training data, to cheat the matcher.

2.3 Distortion Detection Based on Special Hardware

It is necessary to automatically detect distortion during Fingerprint acquisition so that extremely distorted fingerprints can be rejected. Many researchers have recommended detecting improper force using specially designed hardware [14], [15], [16]. Bolle et al. [14] proposed to detect excessive force and torque exerted by using a force sensor. They display that controlled fingerprint acquisition leads to enhanced matching performance [15]. Fujiiproposed to detect distortion by detecting deformation ofa transparent film [16] attached to the sensor surface. Doraiet al. [17] planned to detect distortion by analyzing the change in video of fingerprint. However, the above methods have the following restrictions :(i) they need to special force sensors or fingerprint sensors with attached the video capturing capability; (ii) they cannotdetect distorted fingerprint images in original existing fingerprintdatabases; and (iii) they cannot detect fingerprints distorted before pressing on the sensor.

2.4 Distortion Rectification Based on Finger-Specific Statistics

Ross et al. [17] learn the deformation pattern from collectionsof training images of the same finger and transform the template with the moderate deformation. They show this leads to huge minutiae matching accuracy.

But this method has the following restrictions: (i) to taking themultiple images of the same finger is inconvenient in some applications and existing fingerprint databases generally contain only one image per finger; and (ii) even if multiple images per finger are available, it is not necessarily sufficient to cover various skin distortions.

3. A proposed Approach:

In Proposed System was evaluated at two levels of plane: finger level and subject level. At the finger level, we estimate the performance of differentiating between natural and changed fingerprints. At the subject level, we estimate the performance of differentiatingbetween subjects with natural fingerprints and those with changed fingerprints.

The proposed algorithm is based on the characteristics extracted from the orientation field and minutiae perform or satisfy the three required requirements for alteration detection algorithm: 1) speedy operational time, 2) Huge true positive rate at small false positive rate, and 3) Ease of integration into AFIS.

4. Methodology:

4.1 Detection of Altered Fingerprints

4.1.1 Normalization:-

An input fingerprint image which is provided is normalizedby cropping or cutting a rectangularregion of the input image fingerprint, which is located atthe center of the fingerprint and aligned along with thelongitudinal direction of the fingerprints, using the NISTBiometric Image Software (NBIS). This stepinsures that the features extracted in the subsequentsteps are invariant with respect to translation androtation of finger.

4.1.2 Orientation Field Estimation

The orientation field ofthe fingerprint is estimated using thegradient-based method. The starting orientationfield is smoothed moderating filter,followed by moderating the orientations in pixel blocks. A foreground mask is earn bymeasuring the dynamic range of gray values of thefingerprint image in local blocks and morphologicalprocess for filling holes and removing isolatedblocks is performed**.**

4.1.3 Orientation Field Approximation

The orientationfield is near by a polynomial modelto obtain.

4.1.4 Feature Extraction

The error map is counted as the absolute difference in-between and used to construct the feature vector.

4.2 Analysis of Minutiae Distribution:

In this methodology, a minutia in the fingerprint implies the ridge characteristics such as ridge ending or ridge bifurcation. Almost all the fingerprint recognition systems usage minutiae for matching. The abnormality observed in orientation field also noted that minutiae distribution of altered fingerprints often differs from that of natural fingerprints. On the basis of minutiae extracted from a fingerprint by the open source minutiae extractor in NBIS, a minutiae density map is composed by using the Parzen window method containing uniform kernel function.

5. Conclusion

Wrong non-match rates of fingerprint matchers are very huge in the case of critically distorted fingerprints. This creates a security hole in automatic recognition of fingerprint systems which can be utilized by criminals and terrorists. For this reasoning, it is required to develop a fingerprint distortion detection and rectification algorithm, to fill the hole. The distorted fingerprint detection and rectificationpaper described a novel distorted fingerprint detection and rectification algorithm. For distortion detection, the ridge orientation map and period map of a fingerprint are needed as the feature vector and a SVM classifier is skilled to categorize the input fingerprint as distorted or normal. (Not distorted). For distortion rectification a close neighbor regression approach is used to conclude the distortion field from the provided input distorted fingerprint and then the converse of the distortion field is used to convert the distorted fingerprint into a normal one (un-distorted). The experimental results on FVC2004 DB1, Tsinghua DF database, and NIST SD27 database displayed that the scheduled algorithm can increasethe recognition rate of distorted fingerprints manifestly. The proposed algorithm based on the features derived from the orientation field and minutiae amuse the three necessary requirements for change detection algorithm:

A major restriction (limitation) of the current approach is efficiency. Both means detection and rectification steps can be significantly pace up if a tough and correctly fingerprint register algorithm can be created. Another limitation (restriction) is the current approach is not supported rolled fingerprints. It is crucial to collect many rolled fingerprints with several distortion types and meanwhile to get accurate distortion fields for learning statistical distortion model. It is our work to solve the above drawback (limitations).

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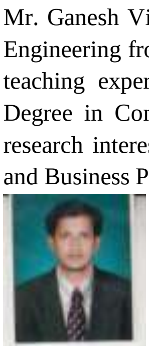

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