Detecting Fingerprint Distortion from a Single Image

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***Abstract*—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. Promising results are obtained on a public domain fingerprint database containing distorted fingerprints.**

I. INTRODUCTION

Although automatic fingerprint recognition technologies have rapidly advanced during the last forty years, there still exists several challenging research problems, for example, recognizing low quality fingerprints. Fingerprint matcher is very sensitive to image quality as observed in the FVC2006 [1], where the matching accuracy of the same algorithm varies significantly among different datasets due to variation in image quality. The difference between the accuracies of plain, rolled and latent fingerprint matching is even larger as observed in technology evaluations conducted by the NIST [2].

A number of factors may contribute to the degradation of fingerprint image quality, including small finger area, cuts and abrasions on the finger, wet or dry finger, dirt on the finger or sensor, and skin distortion.

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 enrollment under different names, the user of interest (e.g. criminals) 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,

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Fig. 1. The low capability of existing techniques in matching and detecting distorted fingerprints generates a serious security hole in fingerprint-based person recognition systems. These two images in FVC2004 DB1 are from the same finger. The right one contains severe distortion as illustrated by the corresponding triangles. The match score between these two images computed by a well-known commercial fingerprint matcher, VeriFinger, is 0. According to the well-known NIST fingerprint image quality (NFIQ) assessment algorithm, the quality level of both images are 1, the highest level.

since malicious users may purposely reduce fingerprint quality to prevent fingerprint system from finding the true identity [3]. In fact, law enforcement officials have encountered a number of cases where criminals attempted to avoid identification by damaging or surgically altering their fingerprints [4].

Hence it is especially important for negative fingerprint recognition systems to detect low quality fingerprints so that the fingerprint system is not compromised by malicious users. A widely used fingerprint quality control software is the well-known NIST fingerprint image quality software (NFIQ) [5]. However, skin distortion, a very important quality factor, is not considered in NFIQ as well as other fingerprint quality assessment algorithms [6]. For example, the NFIQ value of the right fingerprint in Fig. 1, which is severely distorted, is 1, the highest quality level. Note that, for a negative fingerprint recognition system, its security level is as weak as the weakest point. Thus it is urgent to develop a distorted fingerprint detection algorithm to fill the hole of current fingerprint quality assessment techniques.

Elastic distortion is introduced due to the inherent flexibility of fingertips and contact-based fingerprint acquisition procedure. Since the shape of fingertips is not flat, the surface of fingers has to be pressed onto the surface of fingerprint sensor or paper. Distortion is unavoidably introduced in this procedure. Although several contactless fingerprint acquisition techniques have been introduced recently [7], contact-based techniques are still the dominating one, especially in law enforcement applications. Distortion in different fingerprint images of the same finger is usually different due to variations in contact area, direction and force of pressure. Inconsistent 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 distorted fingerprints (see Fig. 1 for an example). So it is the inconsistence of distortion rather than the distortion itself that causes false non-matches. To alleviate the problem caused by inconsistent distortion, the user should press the finger in a common and comfortable way. For example, the finger should be horizontal to the sensor/paper surface and the direction of press force is vertical to the sensor/paper surface. Such requirement is analogous to those in face recognition systems where the user is required to have a frontal pose and a neutral expression. However, there must be a proper way to enforce such requirement since (1) we cannot expect malicious users to follow the requirement and (2) most of the users in many negative recognition systems, such as border control systems, are not criminals.

The rest of the paper is organized as follows. In section II, we review related work. The details of the proposed approach are given in section III and experimental results are presented in section IV. Finally, we summarize the paper in section V.

II. Related Work

Existing techniques for handling distortion can be coarsely classified into four categories.

A. *Distortion-Tolerant Matching*

The most popular way to handle distortion is to make the matcher tolerant to distortion [8]–[10]. In other words, they deal with distortion for every pair of fingerprints to be compared. For example, 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 [8] to compensate for distortion; (ii) explicitly model the spatial transformation by Thin-Plate Spline model [9]; and (iii) only enforce constraint on distortion locally [10].

However, allowing larger distortion in matching will inevitably result in higher false match rate. For example, if we increased the bounding zone around a minutia, many non-matched minutiae will have a chance to get paired.

B. *Fingerprint Adjustment*

Senior and Bolle [11] deal with distortion by normalizing ridge density in the whole fingerprint to a fixed value. They showed this can improve genuine match scores. However, ridge density is known to contain discriminating information and several researchers have reported improved matching accuracy due to incorporating ridge density information into minutiae matchers [12], [13]. Simply unifying ridge density of all fingerprints will lose discriminating information in fingerprints and may increase false match rate.

Ross et al. [14] learn the deformation pattern from a set of training images of the same finger and transform the template with the least deformation using the average deformation with other images. 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; and (ii) even if multiple images per finger are available, a malicious person can still adopt unusual distortion, which is not reflected in the training data, to cheat the matcher.

C. *Proper Sensor Design and Operation*

Another way of reducing distortion is to properly design the sensor and correctly perform the acquisition. Singer-finger scanner with properly designed moundings around the sensor can mechanically constrain the force and torque within an acceptable range. Capturing four fingers simultaneously using tenprint scanners may also reduce distortion. Police staff responsible for fingerprinting suspects may follow a standard procedure to record fingerprints so that the relative distortion between different images of the same finger is small.

However, this type of method has some limitations: (i) it cannot handle distorted fingerprints in existing fingerprint databases; (ii) fingerprint operators in non-forensic applications typically did not receive as much training as operators in forensic applications; (iii) controlled fingerprinting as done in law enforcement agencies is not acceptable in civilian or governmental applications where most of the users are not criminals; and (iv) malicious users may distort the finger skin using some chemical techniques or surgically.

D. *Distortion Detection*

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 [15]–[17]. Bolle et al. [15] proposed to detect excessive force and torque exerted by using a force sensor. They showed that controlled fingerprint acquisition leads to improved matching performance [16]. Fujii [17] proposed to detect distortion by detecting deformation of a transparent film attached to the sensor surface. Dorai et al. [18] proposed to detect distortion by analyzing the motion in video of fingerprint.

However, the above methods have the following limitations: (i) they require special force sensors or fingerprint sensors with video capturing capability; (ii) they can not detect distorted fingerprint images in existing fingerprint databases; and (iii) they cannot detect fingerprints which are distorted before pressing on the sensor.

III. Proposed Approach

The proposed approach falls into the fourth category, distortion detection. However, different from existing distortion detection approaches, our approach can detect distortion based

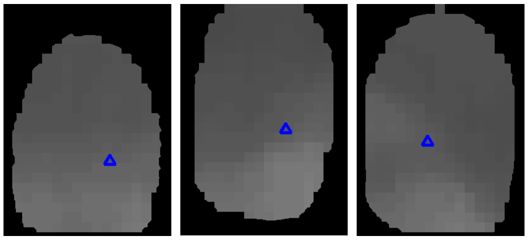
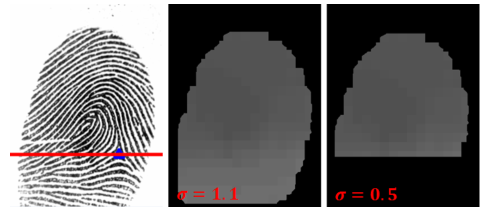
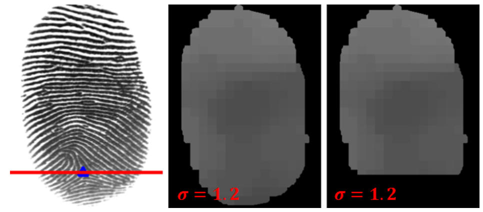


Fig. 2. Ridge period images of three normal fingerprints. The blue triangle indicates the location of delta point. Ridge period below the delta is larger (brighter) than the rest region.



(a) Normal fingerprint



(b) Distorted fingerprint

Fig. 3. Advantage of computing the standard deviation of ridge period only in the top region. (a)/(b) contains the normal/distorted fingerprint, its period image and the cropped period image. The blue triangle is the delta point and the red line is the separating line. The difference of σ between the two fingerprints becomes more obvious after cropping.

Fig. 4. Three cases in cropping the fingerprint for computing standard deviation of ridge period: (i) delta is detected; (ii) delta is missing but the core is detected; and (iii) no singular points are detected. The blue circle is the core, the blue triangle is the delta, and the red line is the separating line.

on a single fingerprint image which is obtained using traditional fingerprint sensing techniques. An important merit of the proposed approach is that it can be easily incorporated into existing automatic fingerprint recognition systems, since it (i) does not require designing new fingerprint sensors; (ii) can detect distorted fingerprints in existing fingerprint databases; and (iii) does not require any change of fingerprint matchers.

Given a grayscale fingerprint image, the proposed algorithm computes a distortion degree, a real number in $[0, 1]$, by analyzing its ridge period image and ridge orientation field. The ridge period image and orientation field are estimated from the skeleton image outputted by VeriFinger. In the following subsections, we describe distortion estimation based on ridge period image, ridge orientation field, and their fusion.

A. Ridge Period

A common assumption used in several related work [11] is that the ridges in a normal fingerprint[1] are constantly spaced. If a fingerprint is severely distorted, the above assumption will be violated. Based on this assumption, the standard deviation σ of ridge period in the whole fingerprint image can be used to distinguish distorted fingerprints from normal fingerprints.

However, after examining many fingerprints, we noticed that ridge period in normal fingerprints is not uniform. As can be observed from the ridge period images of three normal fingerprints in Fig. 2, ridge period below the delta is generally larger than that in the other region. σ in the whole fingerprint is not a good feature for detecting distortion. So we first detect the delta point using VeriFinger and draw a horizontal separating line passing through it. Only the region above the separating line is used to compute σ. As shown in Fig. 3, σ in the cropped fingerprint is better than in the whole image in distinguishing distorted fingerprints from normal fingerprints.

If there is no delta points detected, we draw a separating line passing through the middle point between the lower core point and the lower boundary of the foreground area. If there is no singular points detected, the separating line is set as the line passing through the vertical center of the finger. These three cases are shown in Fig. 4.

[1]A fingerprint is called a normal fingerprint if it is captured in a normal manner, i.e., the finger is parallel to the sensor surface and the pressing force is vertical to the sensor surface.

B. Ridge Orientation

A fingerprint can be roughly segmented into three regions: the top region, the middle region, and the bottom region. Singular points always appear in the middle region. Since fingerprint pattern (arch, loop, whorl) classification is based on the orientation field in the middle region, this region is also termed as the pattern area in the literature. The orientation field in the top and bottom region of finger is similar among different fingerprints as we can see from the ridge orientation fields shown in Fig. 5. Since we have observed that distortion tends to occur in the top region, we consider only the orientation field in this region for detecting distortion.

The top region of a fingerprint is determined as follows. If a top core point is detected by VeriFinger, we regard the parts above the top core point as the top region. If there is no core points detected, the part above the vertical center of the finger is regarded as the top region.

Ridges in the top region of a normal fingerprint are of concave shape with certain curvature. However, we noticed that in many severely distorted fingerprints, ridges in the top region have a smaller curvature and sometimes they even

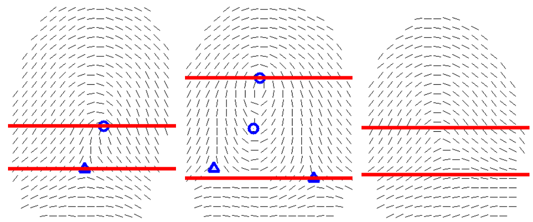
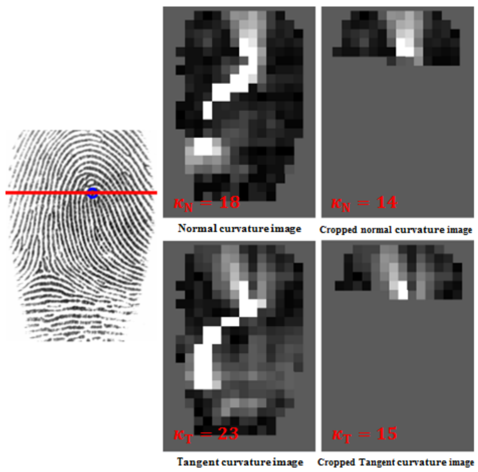
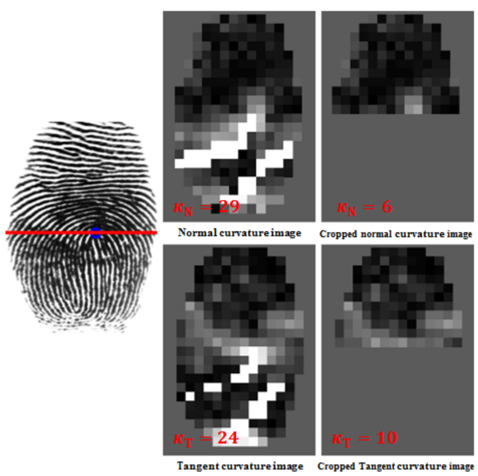


Fig. 5. Orientation field of three patterns: loop, whorl, and arch. A fingerprint is separated into three regions by the two red separating lines.



(a) Normal fingerprint



(b) Distorted fingerprint

Fig. 6. Advantage of computing the mean curvature only in the top region. Before cropping, the mean curvature of the distortion fingerprint is larger. But after cropping, the mean curvature of the normal fingerprint is larger.

become convex. So we compute the normal curvature image and the tangent curvature image of a fingerprint. The means κ_{N} and κ_{T} of the two curvature images are used as the features. An example is given in Fig. 6 to show the necessity of using only the curvatures in the top region for detecting distortion.

The definition of normal curvature and tangent curvature at a point O is illustrated in Fig. 7. A local coordinate system is defined using O as the origin and the local ridge

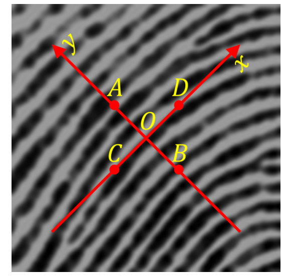


Fig. 7. Normal curvature at point O is computed as the angle between local ridge orientation at point A and point B. Tangent curvature at point O is computed as the angle between local ridge orientation at point C and point D.

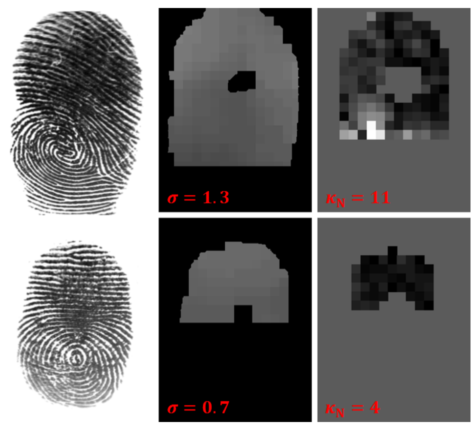


Fig. 8. Advantage of fusing ridge period and curvature information for distortion estimation. The left/middle/right column contains the distorted fingerprint, its period image and its normal curvature image. The top distorted fingerprint cannot be detected based only on the curvature image, while the bottom distorted fingerprint cannot be detected based only on the period image. Due to fusion, both fingerprints are correctly detected as distorted fingerprints.

orientation $\theta(O)$ as the direction of x axis. The coordinates of points A, B, C, D in the local coordinate system are $(0, \lambda), (0, -\lambda), (-\lambda, 0), (\lambda, 0)$, where λ is empirically set as 24 pixels. The angle between $\theta(A)$ and $\theta(B)$ is termed as the normal curvature. The angle between $\theta(C)$ and $\theta(D)$ is termed as the tangent curvature.

C. Fusion

Considering that the discriminating power of each of the three features alone is limited, we use the weighted sum rule to fuse the three features into a distortion degree

$$d = w_1\sigma' + w_2(1 - \kappa'_{\mathrm{N}}) + w_3(1 - \kappa'_{\mathrm{T}}), \tag{1}$$

where σ', κ'_{N}, κ'_{T} are the normalized features in the range $[0, 1]$ using the min-max normalization, and the weights are empirically set as 0.2, 0.5, 0.3. We chose this simple fusion rule because it does not require a large number of samples for training. Two examples are given in Fig. 8 to show the advantage of the fusion.

IV. Experiments

The proposed algorithm can be used in two ways: (i) detecting severely distorted fingerprints as a standalone module; or (ii) combining with existing fingerprint quality assessment algorithms to form a more accurate quality measure. Hence two experiments were conducted to evaluate the proposed algorithm.

A. Detection of Distorted Fingerprints

Since there is no public domain fingerprint dataset where distorted and normal fingerprints are labeled, we use the following procedure to label distorted and normal fingerprints in public domain datasets. The filenames of selected images will be made publicly available so that other interested researchers can evaluate their approaches on the same dataset.

Normal fingerprint samples are taken from DB1_A of FVC2002. This database is selected because it contains relatively few distorted fingerprints. This database contains 800 fingerprints from 100 fingers and 8 impressions per finger. To make sure the independence of the samples, we just use one sample from each finger. The following procedure is used to select one normal fingerprint from each of the 100 different fingers. Firstly, VeriFinger is used to find the matching minutiae between any two mated fingerprints. Then we estimate a rigid transformation using the matching minutiae and align the minutiae of one fingerprint w.r.t. the other one. A distortion score is computed as the mean distance between matching minutiae. For every finger, we select the impression whose distortion score with other impressions of the same finger is minimum as the normal fingerprint.

Distorted fingerprint samples are taken from DB1 of FVC2004, which contains 880 fingerprints from 110 fingers and 8 impressions per finger. The procedure of obtaining distorted samples is similar to the procedure of obtaining normal samples. The only difference is that we select the fingerprint with the maximum distortion score as the distorted sample. Note that this procedure cannot find all distorted fingerprints since the matching minutiae found by VeriFinger for many distorted fingerprints are wrong. So we also manually removed some incorrectly selected fingerprints and added missed distorted fingerprints. Finally, we obtained 75 distorted samples. All distorted fingerprints shown in this paper are from these 75 images. Among all 523 genuine matches associated with these 75 distorted fingerprints, the matching scores of 34.8% of them are 0 according to VeriFinger. This indicates that distorted fingerprint is indeed a challenging problem even for well optimized commercial fingerprint matchers.

Based on this dataset of normal and distorted fingerprints, we conducted a classification experiment using the proposed distortion detector. A distorted fingerprint is called a positive sample and a normal fingerprint is called a negative sample. A sample is classified as a positive sample if its distortion degree computed by the proposed algorithm is above a predefined threshold. 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 varying the threshold value, we obtained a set of true positive rates (TPR) and false positive rates (FPR), which can be plotted as a Receiver Operating Characteristic (ROC) curve.

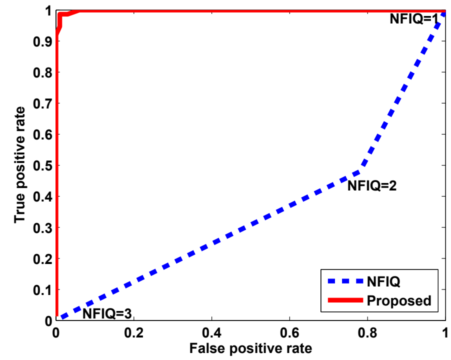


Fig. 9. ROC curves of the proposed method and the NFIQ algorithm in detecting distorted fingerprints in a dataset consisting of 75 distorted fingerprints and 100 normal fingerprints. Since very few fingerprints in this dataset has NFIQ values larger than 2, the only one feasible threshold value for NFIQ is 2. At this threshold, the FPR of NFIQ is as high as 78% and its TPR is only 48%.

The ROC curves of the proposed method and the NFIQ algorithm are given in Fig. 9. Since NFIQ has only five different values, with 1 being the highest quality and 5 being the lowest quality, its ROC curve is only valid at several points. In fact, very few fingerprints in this dataset has NFIQ value larger than 2. Therefore, the only feasible threshold value for NFIQ is 2. At this threshold value, the FPR of NFIQ is as high as 78% and its TPR is only 48%. In contrast, the proposed algorithm can achieve 98.67% TPR at 1% FPR. This experiment shows that that the proposed method outperforms the NFIQ algorithm significantly in detecting distorted fingerprints..

B. Assessment of Fingerprint Quality

The proposed algorithm can be viewed as a fingerprint quality assessment algorithm, although it considers only one aspect of fingerprint quality, namely distortion. A recommended method for evaluating fingerprint quality assessment algorithms in [19] is to combine the quality assessment algorithm with a fingerprint matcher and report the False Non-Match Rate (FNMR) versus Reject Rate (RR) curve. A good quality assessment algorithm should be able to significantly reduce the FNMR by only rejecting a small number of poor quality images. Since the proposed distortion estimation algorithm is aimed at filling the gap of existing fingerprint quality assessment algorithms, we need to examine whether a combination of the proposed algorithm and the NFIQ algorithm performs better than NFIQ alone. In this experiment, two quality assessment algorithms (the NFIQ algorithm, and a max rule fusion[2] of the proposed algorithm and the NFIQ algorithm), the VeriFinger matcher, and all fingerprint images in FVC2004 DB1 are used. The FNMR vs. RR curves of the

[2]For fusion purpose, the NFIQ value has been linearly mapped to [0, 1] with 0 indicating the highest quality.

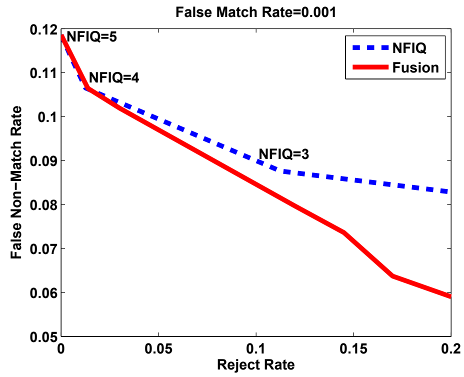


Fig. 10. FNMR vs. Reject Rate curves of the NFIQ algorithm and the fusion of NFIQ and the proposed algorithm on FVC2004 DB1. Since NFIQ has only five different values, its curve is only valid at several points.

Fig. 11. NFIQ algorithm assigns the highest quality level to these three severely distorted fingerprint images. The distortion degrees of these images estimated by the proposed algorithm are, 0.8153, 0.8660, and 0.9465, respectively, indicating that they are severely distorted fingerprints.

NFIQ algorithms and the fusion algorithm are shown in Fig. 10.

Fig. 10 shows that the proposed distortion estimation algorithm does improve the ability of the NFIQ algorithm in detecting and rejecting poor quality fingerprints. At lower reject rates (< 0.05), the NFIQ algorithm can correctly reject very poor quality fingerprints and the proposed algorithm is not helpful. However, at reject rates above 0.05, the contribution of the proposed algorithm becomes evident, indicating that many distorted fingerprints, whose image quality is good, are correctly rejected. Three such examples are given in Fig. 11.

V. Conclusions

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. Since existing fingerprint image quality assessment algorithms, such as the NFIQ algorithm, do not take distortion into account, it is urgent to develop new techniques to detect distorted fingerprints. We proposed a novel approach based on analyzing ridge period and orientation information for detecting the distorted fingerprints. Different from previous distortion detection algorithms, the proposed algorithm can detect distortion from a single image which is obtained using traditional fingerprint sensing techniques. Such properties are very desired in practical applications. Experimental result on a public domain dataset demonstrates that the proposed distortion detector can detect most severely distorted fingerprints at a low false positive rate. We also show that by fusing the proposed distortion estimation algorithm with the NFIQ algorithm, the ability of predicting fingerprint quality is significantly improved.

The current 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. Lastly, this algorithm cannot reliably estimate distortion in latent fingerprints. We plan to overcome the above limitations in the future.

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