Recent progress in fingerprint recognition*

TIAN Jie[1]**, CHEN Xinjian[1,2], ZHANG Yangyang[1,2], YANG Xin[1], HE Yuliang[1,2], LI Liang[1,2], XIE Weihua[1,2] and ZHENG Zhipeng[1,2]

(1. Center for Biometrics and Security Research, Key Laboratory of Complex Systems and Intelligence Science, Institute of Automation, Chinese Academy of Sciences, Beijing 100080, China; 2. Graduate School of the Chinese Academy of Sciences, Beijing 100080, China)

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Abstract Fingerprint recognition has been increasingly used to realize personal identification in civilian's daily life, such as ID card, fingerprints hard disk and so on. Great improvement has been achieved in the on-line fingerprint sensing technology and automatic fingerprint recognition algorithms. Various fingerprint recognition techniques, including fingerprint acquisition, classification, enhancement and matching, are highly improved. This paper overviews recent advances in fingerprint recognition and summarizes the algorithm proposed for every step with special focuses on the enhancement of low-quality fingerprints and the matching of the distorted fingerprint images. Both issues are believed to be significant and challenging tasks. In addition, we also discuss the common evaluation for the fingerprint recognition algorithm of the Fingerprint Verification Competition 2004 (FVC2004) and the Fingerprint Vendor Technology Evaluation 2003 (FpVTE2003), based on which we could measure the performance of the recognition algorithm objectively and uniformly.

Keywords: biometrics, fingerprint, enhancement, matching, minutia, image registration, similarity measures.

Fingerprint has been used for individual identification for a long period. Fingerprints are the patterns formed by ridges and valleys flowing on the skin of fingertips. The fingerprint satisfies all the demanded properties, such as universality, permanence and distinctiveness. First, the fingerprint exists prevalently, that is, each person should have this characteristic. Second, the fingerprint can be maintained invariantly for matching until death. Third, any fingerprint should have the unique feature details. However, this property is not an established fact but an empirical observation. Based on the minutiae-coordinate model, we suppose the minutiae are distributed randomly and discover that the possibility of mistaking different fingerprints is small enough for application.

Fingerprint recognition has been early accepted for identifying criminals in law enforcement, and is being increasingly used to realize personal identification in civilian's daily life, such as ID card, fingerprints hard disk and so on. Various fingerprint recognition techniques, including fingerprint acquisition, classification, enhancement and matching, are developed and advanced rapidly. Depending on the application purpose, we classify the recognition into two categories: identification mode and verification mode[1].

Since fingerprint recognition is usually processed in a huge database, it is highly necessary to investigate an automatic fingerprint identification system (AFIS) for large-scale recognition[2]. AFIS is a pattern recognition system, typically including acquiring fingerprints from individuals, enhancing images, extracting features, comparing the features to that in the database. Fig. 1 shows the typical structure of the recognition system. Currently, most of AFIS utilize the minutiae-coordinate model for individual identification or verification.

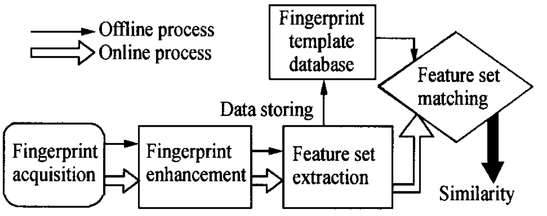

Fig. 1. The typical structure of the recognition system.

This paper overviews the recent progress in fingerprint recognition and summarizes the algorithm proposed for every step, especially focuses on the enhancement of low-quality fingerprints and the matching of the distorted images. Both issues are believed to be significant and challenging tasks. In addition, we also discuss the standard evaluation for the finger-

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** To whom correspondence should be addressed. E-mail: tian@doctor.com

print recognition algorithm, based on which we could measure the performance of the recognition algorithm objectively and uniformly. Firstly, we describe and compare the algorithms of enhancement, especially canvassing the disposure of low-quality fingerprints. We also discuss the most prevalent feature extraction method based on the minutiae pattern. Secondly, we enumerate different methods for fingerprints matching and present the advancement in dealing with the distorted fingerprints. Finally, two international common evaluations for fingerprint recognition algorithms of FVC2004 and FpVTE2003 are introduced.

1 Fingerprint enhancement

AFIS is based on a comparison of the features in details of ridge and valley structure. Among all the features, terminations and bifurcations, which are usually called minutiae, are the most prominent structures used in AFIS. However, in practice, it is very difficult to reliably extract the minutiae from the input image. Automatic and accurate extraction of minutiae from the digital fingerprint image highly relies on the quality of images. Several factors, such as scars, non-uniform contact with the fingerprint sensors, environmental condition during the capturing process, etc., can dramatically degrade the quality of fingerprint images. The main objective of the fingerprint enhancement algorithm is to improve the clarity of ridge structures and reduce the noise present in the image. Therefore, it is necessary to apply the enhancement techniques prior to minutiae extraction to obtain a more reliable estimation of minutiae locations; and it is one of the most significant steps in AFIS[3].

Among most fingerprint enhancement algorithms, the sequence of main stages is described in Fig. 2. Certainly, the embodied steps of different algorithms cannot be the same. For instance, Maio et al.[4] introduced an approach which works with gray level images based on direct ridge following, overleaping the step of binarization and thinning.

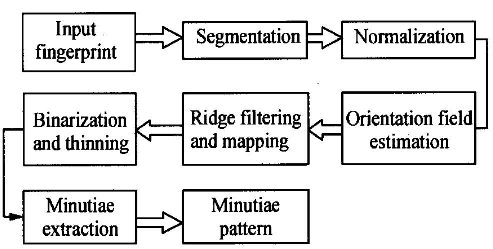

Fig. 2. Complete fingerprint enhancement process.

1.1 Typical fingerprint enhancement

1.1.1 Segmentation

Segmentation is an important step of image preprocessing, which separates the available fingerprint field from the foreground and the noisy region. Effective segmentation not only simplifies the subsequent processing, but also improves the reliability of minutiae extraction considerably.

The general segmentation algorithms are based on the variance threshold. The available fingerprint area exhibits a very high variance value, whereas the other regions have a relatively low variance. Hence, a variance threshold is used to complete the segmentation. Bazen and Gerez[5] proposed a segmentation algorithm based on pixels features, using the criterion of Rosenblatt's perception to classify the pixels. Chen et al.[6] advanced an algorithm by utilizing three block features: the clusters degree, the mean information, and the variance for the segmentation of fingerprints.

There is another type of method[4] based on the orientation information of fingerprint images. The method relies on the reliability of the orientation field, and it is not sensitive to the gray contrast. However, it is almost impossible to get the accurate orientation graph in regions with discontinuous ridges or around the pore and delta.

The frequency domain based method[7] showed that the surface wave model does not hold in the foreground and noisy regions, and there is very little energy existing in Fourier spectrum. However, this algorithm cannot treat the areas consisting of unequal texture resulting from the distortion of fingerprint images.

Recently, merging certain features to gain the segmentation's propriety is evidently feasible. Because of different characteristics, the process has many dubious components. A series of algorithms have been put forward to solve the problem, such as fingerprint segmentation based on D-S Evidence Theory[8], application of Urn Model in image segmentation[9], the Markov Model based segment algorithm[10], and so on.

1.1.2 Normalization

Due to imperfections in the fingerprint image capture process such as non-uniform ink intensity or non-uniform contact with the capture device, a fingerprint image may display distorted levels of variation in grey-level values along the ridges and valleys. Thus, normalization is performed to decrease the dynamic range of the gray scale between ridges and valleys of the image[10], which facilitates the subsequent enhancement steps. Lin et al.[11] standardized the image intensity values by adjusting the range of grey-level values to lie within a desired range of values. The normalization factor is calculated according to the mean and the variance of the image.

1.1.3 Orientation field estimation

According to some fingerprint images, the orientation field is a matrix representing ridge orientation as a directional vector for each pixel. It reflects the fundamental information existing in the fingerprint image, and it is a significant component to measure the fingerprint quality. There are several approaches to calculate it. The widely employed gradient-based approach[11] is based on the fact that the orientation vector is orthogonal to the gradient. In this method, the image is divided into small blocks, and the orientation vector of each block is estimated by averaging the vectors orthogonal to the gradient of all pixels. The template comparison based approach[12] disperses the orientation into finite directions, utilizes a special template to calculate the presumed orientation for the ridge in the block. Compared to the gradient based approach, this approach gains results more quickly at the expense of precision.

Due to the noise and the corrupt field existing in the fingerprint images, it is necessary to postprocess the orientation field. Given that the ridge orientation varies slowly in a local neighborhood, the orientation image is then smoothed by using a low-pass filter to reduce the effect of outliers[13]. Fig. 3 gives an original fingerprint image and its orientation field based on gradient.

Fig. 3. An origin fingerprint image and its orientation field.

1.1.4 Ridge filtering and mapping

Fingerprint image usually contains random noise and coarse ridges because of the imperfect fingers' condition and the environment. It is critical to remove the noise and smooth the ridges by filter to map the ridges accurately. The existing algorithms can be broadly classified into spatial domain based[11,14—18] and Fourier domain based[19—21] methods according to their concrete implementation methods. The former usually employs local ridge properties which consist of ridge frequencies and directions, while the latter mainly utilizs global ridge properties.

Spatial domain based methods handle the band filtering procedure by directly convolving the filter operator with the digital fingerprint image. The representative method introduced by Lin et al.[11] employed a Gabor filter which has frequency-selective and orientation-selective properties. However, it is too time consuming for application. Then, a series of modified algorithms based on Gabor filter were proposed to accelerate the processing. Vutipong et al.[14] implemented a new set of separable Gabor filters for fingerprint enhancement. It is approximately 2.6 times faster than the conventional Gabor filtering.

Fourier domain based methods refer to those coping with the filtering procedure by directly modifying the frequency spectrum of the original image. Since the ridges and valleys present almost equidistantly, the energy of fingerprint images concentrates around a certain frequency. The directional filtering method proposed by Sherlock et al.[19] is a sort of Fourier domain based methods that firstly filter a raw image by a few directional filters, which can transmit the spectrum of a certain direction and attenuate the spectra of other directions, and then form the enhanced image by appropriately combining these filtered images. Compared to Fourier enhancement, spatial domain based methods such as the Gabor filtering are complicated and time consuming in computation.

In addition, there are other algorithms[22] that improve the clarity and continuity of ridge structures based on the multiresolution analysis of global texture and local orientation by the wavelet transform. There are also several dyadic scale-space methods[12,23] which decompose the fingerprint image into a series of images in different scales, and then analyze and organize the image characteristics to realize enhancement reliably.

1.1.5 Binarization and thinning

Binarization is a process that converts a gray-level image into a binary image. It improves the contrast between the ridges and valleys in a fingerprint image, and consequently facilitates the minutiae extraction. The critical issue is to choose a proper threshold to binary the image. The local adaptive threshold based algorithm has been employed to generate the binary image. It includes choosing proper threshold referring to the local image window around each pixel and classifying the pixel as the foreground or the background. He et al.[24] developed a method to quickly and directly binarize the image with its orientation field.

As the final step typically performed prior to minutiae extraction, thinning is a morphological operation that successively erodes away the original ridges until they are one pixel wide. A standard thinning algorithm[25] is performed by using two subiterations.

1.1.6 Minutiae extraction

In this stage, the local features of minutiae from the thinning image are extracted to obtain the fingerprint biometric pattern[13]. The majority of the minutiae extraction algorithms are based upon the skeletons of fingerprint images. Relatively, they are computationally expensive and can produce artifacts such as spurs and bridges. Chikkerur et al.[26] proposed a method for feature extraction based on chain coded contour following. Maio et al.[4] extracted the minutiae directly from the gray scale image. The main idea of their method is to follow the ridge lines on the gray scale image by "sailing" according to the fingerprint directional image. Jiang et al.[27] improved the flexibility of the algorithm based on ridge following.

The extraction process may result in errors which generate the false minutiae and meanwhile miss the genuine minutiae. Therefore, it is necessary to adopt a post processing method to modify the false features. Luo et al.[17] utilized human knowledge on fingerprints to postprocess the condition of ridge break, bridge, blur, and scar, modified spurious minutiae extraction and gained satisfactory performance. The method proposed by Chikkerur et al.[26] is mainly based on the rules below: 1) Merging the minutiae that are within a certain distance of each other and have similar angles; 2) removing all points at the border of the interest region; 3) discarding the minutiae whose direction is inconsistent with the local ridge orientation; and so forth. Then, we gain the minutiae patterns of the input fingerprint images. Fig. 4 presents the extracted minutiae of a thinned fingerprint image with its post-processing result.

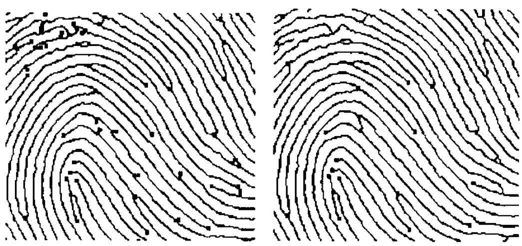

Fig. 4. The extracted minutiae of a thinned fingerprint image with its post-processing result.

1.2 Low-quality fingerprint image enhancement

The quality of fingerprint image degrades due to impression, skin, reader, etc., during image capture. Fig. 5 shows four examples of low quality fingerprints. Generally, the adaptability of the AFIS relies on the availability to enhance poor quality fingerprint images. Such enhancement is so important that it seriously affects the performance of the recognition system. It is one of the most crucial and difficult tasks for fingerprint recognition.

(a) (b) (c) (d)

Fig. 5. Four examples of low quality fingerprints. (a) Too dry; (b) too wet; (c) with many scars; (d) molted.

Image quality analysis is a critical component of a fingerprint live scan workstation. AFIS rejects a certain percentage of submitted fingerprint images because they fail to satisfy the image quality criteria. Failure to extract minutiae points is usually attributed to poor ridge flow, poor contrast and brightness in the image. Shen et al.[28] proposed a Gabor-feature based method to determine the quality of the fingerprint images.

Many standard and special image enhancement techniques have been developed for poor quality images. Shi et al.[29] proposed a new feature Eccentric Moment to locate the blurry boundary using the new block feature of the clarified image for segmentation. Zhou et al.[30] proposed a model-based algorithm which is more accurate and robust to dispose the degraded fingerprints. They compute the coarse orientation field by traditional methods, and approximate the real orientation with smooth curves.

To enhance the poor quality prints efficiently, we must incorporate a robust ridge filter with respect to the quality of input fingerprint images. Lin et al.[11] assumed that the parallel ridges and valleys exhibit some ideal sinusoidal-shaped plane waves associated with some noises, which cannot treat the poor quality images. Yang et al.[15] specified parameters deliberately through some principles instead of experience, preserved fingerprint image structure and achieved image enhancement consistency. This algorithm solved the problem that false estimation of local ridge direction will lead to a poor enhancement. Zhu et al.[31] followed Lin's algorithm, but used a circle support filter and tuned the filter's frequency and size differently. This scheme rapidly enhanced the fingerprint image and effectively overcame the blocky effect. Khan et al.[32] proposed a method using decimation-free directional filter bank (DFB) structure to improve the poor quality fingerprints.

These methods performed local estimation and contextual filtering in a dispersed manner, which often resulted in not only blocky artifacts but also poor estimation of local image characteristics. Another type of mechanism based on nonlinear diffusion was proposed to solve the problem. Xie et al.[18] adopted an image structure tensor merging both the coherence enhancement diffusion[33] for processing flow-like pattern and the forward and backward enhancement diffusion[34] for sharpening ridges. These algorithms utilized the global features of the ridge flow direction to restore the disconnection caused by the poor quality of images and received good performance.

Compared to the uncertainty of local ridge information, the global features can be preserved accurately in the attained fingerprint images. Therefore, many Fourier domain based ridge filters have been presented for the low-quality fingerprint images. Willis et al.[20] proposed a Fourier domain based method that boosts up a low quality fingerprint image by multiplying the frequency spectrum by its magnitude. Zhu et al.[21] combined the two methods mentioned above by multiplying each filter vector with well designed weights to form a new filter vector. In addition, they applied a top-down iteration technique which can make the method more robust.

2 Match algorithm

2.1 Recent advances in fingerprint matching algorithm

A large number of fingerprint matching approaches have been proposed in the literature. These include methods based on point pattern matching, transform features, structural matching, and graph-based matchers.

Many fingerprint recognition algorithms[35—44] are based on minutiae matching since it is widely believed that the minutiae are the most discriminating and reliable features[47,48]. They are essentially "Euclidean" matchers. Fig. 6 shows two fingerprints and the map relations of the corresponding minutiae in these two fingerprints. These matchers assume similarity transformation that there exist translation, rotation and scaling of the minutiae between the input and the template fingerprints, and they can tolerate, to a limited extent, both spurious minutiae and missing genuine minutiae. In addition, some of them can be modified to tolerate a small bounded local perturbation of minutiae. But they cannot handle large distortions of the minutiae from their true locations. Ratha et al.[49] addressed a method based on point pattern matching. The generalized Hough transform is used to recover the pose transformation between two impressions. Chang et al.[37] proposed a generalized Hough transform-based approach which converts point pattern matching to peaks detecting in the Hough space of transformation parameters. It discretizes the parameter space and accumulates evidence in the space by deriving transformation parameters that relate two point patterns using a substructure or feature matching technique. However, if there are only a few minutiae points available, it is difficult to accumulate enough evidence in the Hough transform space for a reliable match. Moreover, it is hard to handle large distortions. Ton et al.[41] proposed a modified version of the relaxation approach[43] to reduce the matching complexity. However, these algorithms are inherently slow because of their iterative nature and unable to handle large distortions. Some researchers proposed the energy minimization method to point pattern matching[35,36,38—40,42], which establishes the correspondence between a pair of point sets by defining an energy function based on an initial set of possible correspondences and utilizes an appropriate optimization technique such as genetic algorithm, neural network, simulated annealing to find a possible suboptimal match. These methods are very slow and unsuitable for a real-time fingerprint identification system.

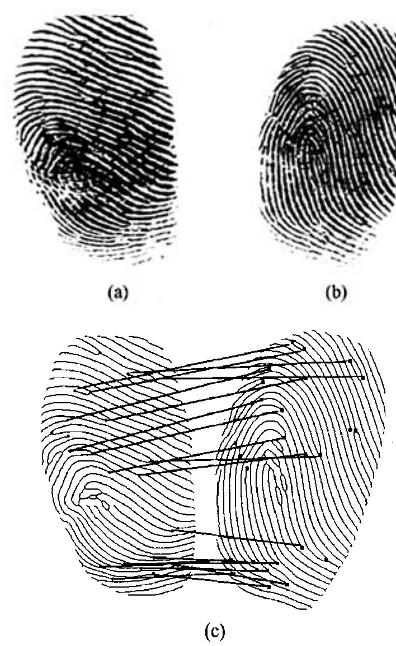

Fig. 6. Minutiae matching of two fingerprints. (a), (b) Original image; (c) the map relations of the corresponding minutiae in fingerprint images (a) and (b), respectively.

Jain et al.[50,51] proposed a novel filterbank-based fingerprint feature representation method. Jiang et al.[52] addressed a method which relies on a similarity measure defined between local structural features to align the two patterns and calculate a matching score between two minutiae lists. Fan et al.[53] applied a set of geometric masks to record part of the rich information of the ridge structure. Wahab et al.[54] addressed a method using groups of minutiae to define local structural features. The matching is performed based on the pairs of corresponding structural features that are identified between two fingerprint impressions. However, these methods do not solve the problem of non-linear distortions.

Some researchers proposed the graph-based matchers[55—57], which are essentially a "topological" type of matchers. They allow general transformations, positional errors, missing minutiae, and spurious minutiae. The performance of these algorithms depends heavily upon the availability of the ridge features and external alignment information. In a semi-automatic fingerprint identification system, these algorithms can perform well since the minutiae patterns can be aligned and the errors in minutiae and ridge features can be corrected interactively. However, a fully automatic fingerprint matching system may not always guarantee the availability of the correct ridge features and external alignment information.

2.2 Distorted fingerprints matching

How to cope with these non-linear distortions in the matching process is a challenging task. According to Fingerprint Verification Competition 2004 (FVC2004)[58], the organizers are particularly insisted on: distortion, dry and wet fingerprints. Distortion of fingerprints seriously affects the accuracy of matching. There are two main reasons contributed to the fingerprint distortion. First, the acquisition of a fingerprint is a 3D-2D warping process[45,46]. The fingerprint captured with different contact centers usually results in different warping mode. Second, distortion will be introduced to fingerprint by the non-orthogonal pressure exerted on the sensor. Fig. 7 displays two examples of large distortion between fingerprints.

Recently, some algorithms have been presented to deal with the non-linear distortion in fingerprints explicitly in order to improve the matching performance. Ratha et al.[61] proposed a method to measure the forces and torques on the scanner directly, which prevents capturing with the aid of special hardware when excessive force is applied to the scanner. Dorai et al.[62] proposed a method to detect and estimate distortion occurring in fingerprint videos. However, the two methods mentioned above do not work with

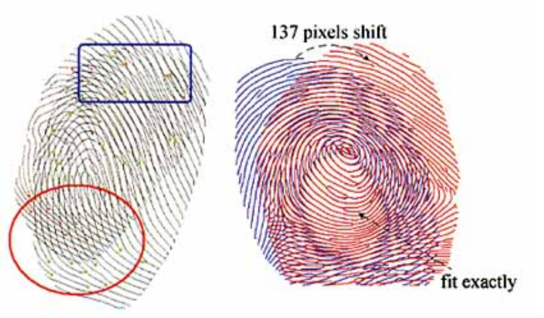

Fig. 7. Two examples of large distortion. (a) In the blue rectangle region, the corresponding minutiae are approximately overlapped, while in the red ellipse region, the maximal vertical difference of the corresponding minutiae is above 100 pixels; (b) in the center region, the corresponding minutiae are approximately overlapped, while in the upper region, the maximal horizontal difference of the corresponding minutiae is 137 pixels.

the collected fingerprint images. Cappelli et al.[45] proposed a plastic distortion model to cope with the nonlinear deformations characterizing fingerprint images taken from on-line acquisition sensors. This model helps to understand the distortion process. However, it is hard to automatically and reliably estimate the parameter due to the insufficient and uncertain information. Lee et al.[63] addressed a minutiae-based fingerprints matching algorithm using distance normalization and local alignment to deal with the non-linear distortion. However, rich information of the ridge/valley structure is not used, and the matching performance is moderate. To improve the matching accuracy, Senior et al.[64] proposed a method to convert a distorted fingerprint image into an equally ridge spaced fingerprint before matching. However, the assumption of equal ridge spacing is less likely to be true for fingerprints—particularly where ridges break down, such as around minutiae or near the edge of the fingerprint. Watson et al.[65] proposed a method to improve the performance of fingerprint correlation matching by distortion tolerant filters. The improvement was achieved by multiple training fingerprints and a distortion-tolerant MINACE filter. However, the algorithm is difficult to realize on line. Vajna[66] also proposed a method based on triangular matching to cope with the strong deformation of fingerprint images, which graphically demonstrates that the large cumulative effects can be resulted from the small local distortions. Bazen et al.[67] employed a thin-plate spline model to describe the non-linear distortions between the two sets of possible matching minutiae pairs. By normalizing the input fingerprint with respect to the template, this method is able to perform a very tight minutiae matching. Ross et al.[68] used the average deformation computed from fingerprint impressions originating from the same finger based on thin plate spline model to cope with the non-linear distortions. Chen et al.[46] introduced a novel fingerprint verification algorithm based on the determination and inspection of the registration pattern (RP) between two fingerprints. The algorithm first coarsely aligns two fingerprints, then determines the possible RP by optimally registering each part of the two fingerprints, and next, inspects the possible RP with a genuine RP space. If the RP makes a genuine one, a further fine matching is conducted. Different from the above mentioned methods, Chen et al.[69] proposed an algorithm based on fuzzy theory to deal with the non-linear distortion in fingerprint images. The local topological structure matching was introduced to improve the robustness of global alignment. And a similarity computing method based on fuzzy theory, normalized fuzzy similarity measure, was conducted to compute the similarity between the template and input fingerprints. Experimental results indicate that the algorithm works well with the non-linear distortions. For deformed fingerprints, the algorithm gives considerably higher matching scores compared to conventional matching methods.

3 Performance evaluation

In the last decade, with the rapid development of fingerprint recognition system, it is urgent to establish a common benchmark in this field. Participators could evaluate their algorithms on this common benchmark, compare the performance and provide an overview of the state-of-the-art technology in fingerprint recognition. There are two internationally authorized and accredited evaluation: Fingerprint Verification Competition (FVC[58—60]) and Fingerprint Vendor Technology Evaluation (FpVTE[71]).

The FVC2004[58] (the Third International Fingerprint Verification Competition) was organized by the Biometric System Laboratory of University of Bologna, the Pattern Recognition and Image Processing Laboratory of Michigan State University and San Jose State University. The aim of FVC2004 is to track recent advances in fingerprint verification, for both academia and industry, and to benchmark the state-of-the-art technology in fingerprint recognition. FVC2004 results were presented at the International Conference on Biometric Authentication (ICBA

2004), January 8—10, 2004. The results of this competition give a useful overview of the state-of-the-art technology in this field. The first and second international competitions on fingerprint verification (FVC2000 and FVC2002[59,60]) were conducted in 2000 and 2002, respectively. These events received great attention both from academic and industrial biometric communities. The FVC established a common benchmark allowing developers to unambiguously compare their algorithms, and provided the overview of the most recent advancement in fingerprint recognition.

The FVC2004 competition focuses on fingerprint verification software. Participators are required to propose two executable programs for corresponding sub-competitions (open category and light category), which were operated on the same databases[70]. In open category, the enrollment response time was limited in 10 s and the match time was less than 5 s for testing. The computing resource for light algorithm was constrained. The limits were as follows: the enrollment time is less than 0.5 s, the matching time is less than 0.3 s, the template size is lower than 2 KB, and the amount of memory allocated is lower than 4 KB. Four fingerprint databases were established for testing, which were collected from three different sensors. Each one has different image sizes and consists of 110 fingers, 8 prints per finger. The algorithm was performed in both genuine mode and imposter mode. For each database, the matching number was 2800 and 4950 times for genuine and imposter matching, respectively. For each algorithm performed in the competition, the statistic performance results were presented by the following performance indicators[67]: 1) Rate of rejecting to enroll (REJENROLL), rate of rejecting to match (REJNGRA and REJNIRA); 2) genuine and impostor score histograms; 3) FMR(t) and FNMR(t) and ROC(t); 4) equal error rate (EER), FMR100, FMR1000, ZeroFMR and ZeroFNMR; 5) average match time and average enroll time; 6) maximum memory allocated for enrollment and for match; 7) average and maximum template size.

The Fingerprint Vendor Technology Evaluation (FpVTE) 2003[71] was an independently administered technology evaluation for fingerprint matching, identification, and verification systems. FpVTE 2003 was conducted by the National Institute of Standards & Technology (NIST) on behalf of the Justice Management Division (JMD) of the U.S. Department of Justice. FpVTE was designed to assess the capability of fingerprint systems to meet requirements for both large-scale and small-scale databases in real world applications. FpVTE 2003 consisted of multiple tests performed with the combinations of fingers (e.g. single fingers, two index fingers, four to ten fingers) and different types and qualities of operational fingerprints (e.g. flat livescan images from visa applicants, multi-finger slap livescan images from present-day booking or background check systems, or rolled and flat inked fingerprints from legacy criminal databases).

Compared to FVC, FpVTE 2003 has many different features, which can reflect the algorithm from other aspects. Small to large-scale fingerprint databases are provided for measuring the algorithms' flexibility. FpVTE consisted of three separate segments, which are Large-Scale Test (LST), Medium-scale Test (MST), and Small-Scale Test (SST)[70]. Table 1 illustrates the relative surroundings for each of them.

Table 1. The relative surroundings of each test

	LST	MST	SST
Finger-mode	Multi-finger	Single-finger	Single-finger
Fingerprint type	Rolls, Slaps, and Flats (Paper and livescan)	Slaps, and Flats (Livescan only)	Flats (Livescan only)
Sample-model	64000 sets of 1—10 fingerprints	10000 fingerprints (all right index finger)	1000 fingerprints (all right index finger)
Time limit	21 days	14 days	14 days

The performance was measured through the following indicators: 1) Match and Non-Match distribution; 2) ROC(t); 3) slice chart; 4) effect of fingerprint quality; 5) effect of finger -mode, and so on.

4 Conclusion

In the last decade, great improvement has been achieved in the development of on-line fingerprint sensing techniques and automatic fingerprint recognition algorithms. This paper overviews recent advances in fingerprint recognition system and summarizes the algorithm proposed for every step including segmentation, normalization, orientation field estimation, ridge filtering and mapping, binarization and thinning, minutiae extraction and fingerprint matching. We especially focus on the enhancement of low-quality fingerprints and the matching of the distorted fingerprint images. Both issues are significant and challenging tasks in fingerprint recognition since they seriously affect the overall performance of the whole recognition system. We also discuss the common evaluation for the fingerprint recognition algorithm by FVC2004 and fpVTE2003, based on which the recognition algorithm could be measured objectively and uniformly.

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