A Performance Evaluation of Fingerprint Minutia Descriptors

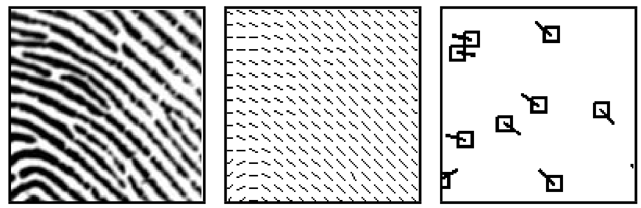
Jianjiang Feng and Jie Zhou
Department of Automation
Tsinghua University, Beijing, China
Email: {jfeng,jzhou}@tsinghua.edu.cn

***Abstract*—Minutiae-based matching method is the most widely used fingerprint matching method and most minutiae matching algorithms employ minutia descriptors of certain type. A good minutia descriptor should be distinctive and at the same time robust in difficult situations, i.e., noise, occlusion and plastic distortion. Many different minutia descriptors have been proposed in the literature, which can be coarsely classified into three categories: image-based, texture-based, and minutia-based. These descriptors have not been evaluated systematically. In this paper, seven different descriptors are evaluated according to local matching accuracy for four types of fingerprint pairs: good quality, poor quality, small common region, and large plastic distortion. Experimental results show that the texture-based descriptor and Minutia Cylinder-Code (MCC) are the two most accurate descriptors. In the case of small common region, texture-based descriptor ranks first, while in the rest three cases, MCC is the most accurate one.**

I. INTRODUCTION

Automated Fingerprint Identification Systems (AFIS) developed for law enforcement applications are mainly based on matching minutiae points in fingerprints, which are the termination and bifurcation of ridges. In recent years, fingerprint recognition systems have been increasingly used in various civilian and government applications, which pose some new challenges to fingerprint recognition technologies, such as fully automatic operation, real-time response, reduced image size or resolution. To resolve these problems, many new representation schemes and matching algorithms have been proposed for fingerprints [1], [2], [3]. However, minutiae-based method is still the most widely adopted method, as shown in FVC2004 [4]. This phenomenon may be due to the fact that minutiae information is highly discriminating and other information can be conveniently incorporated in a minutiae-based matching algorithm.

A typical minutiae matching algorithm consists of two stages: local matching and global matching. In the local matching stage, each minutia in the first fingerprint (query) is compared to each minutia in the second fingerprint (template) to find candidate minutia pairs. In the global matching stage, minutiae sets of the two fingerprints are aligned and a set of minutia pairs is determined as the final matching minutiae pairs. Local matching is very important for the final matching result. Ideally, local matching should output all correct pairs and as few as possible false pairs with low computational complexity.



(a) (b) (c)

Fig. 1. Three types of minutia descriptors. (a) Image-based, (b) texture-based, and (c) minutiae-based.

Most minutiae extraction algorithms attach a minutia with three attributes: x, y coordinates and direction. Since the relative pose between two fingerprints is unknown beforehand for the minutiae matcher, the correspondence between minutiae is very ambiguous and each minutia in the query fingerprint may be matched to any minutia in the template fingerprint. To reduce the ambiguity of correspondence, additional distinguishing information should be attached to a minutia, which is referred to as minutia descriptor. A good minutia descriptor should be distinctive and at the same time robust in difficult situations, i.e., noise, occlusion, and plastic distortion. In other words, a good minutia descriptor should be effective in distinguishing between intra-class and inter-class variations.

Many minutia descriptors have been proposed in the literature. They can be coarsely classified as image-based [1], [5], texture-based [2], [6], [7], and minutiae-based [3], [8], [9], [10], [11], [12], [13], [14]. Since these descriptors have not yet been evaluated systematically, it is unclear which one is more distinctive and which one is more robust. With the increasing deployment of fingerprint recognition systems in various applications, which tend to have different requirements in terms of accuracy, speed, storage space, and privacy, understanding the strengths and weaknesses of various minutia descriptors becomes increasingly important.

In this paper, seven different minutia descriptors are implemented and evaluated according to local matching performance for four types of fingerprint pairs: good quality, poor quality, small common region, and large plastic distortion. Four of the descriptors are minutiae-based, two are texture-based, and one is image-based. This work is partially inspired by the work of Mikolajczyk and Schmid [15], where a set

978-1-4577-0490-1/11/$26.00 ©2011 IEEE

of region descriptors for general image matching and object recognition was evaluated. However, the descriptors evaluated in [15], such as SIFT [16] and Shape Context [17], are not suitable for representing and discriminating stripe patterns, like fingerprints and palmprints. Thus a performance evaluation of minutiae descriptors is still necessary.

The content of this paper is organized as follows. In Section 2, three types of minutia descriptors are reviewed. In Section 3, the implementation details of the descriptors are provided. Experimental results and analysis are presented in Section 4. Finally in Section 5, conclusions are made and future directions are suggested.

II. Review of Minutia Descriptors

In this section, three major types of minutia descriptors are reviewed, including image-based, texture-based, and minutiae-based (see Fig. 1 for an illustration). To make the descriptor invariant to rigid transformation (translation and rotation), all these descriptors are represented in a local coordinate system defined by the central minutia (the minutia to be described).

A. Image-based

The most straightforward descriptor is image-based one, which is composed of grayscale values of pixels in the neighborhood of the central minutia. To compare two descriptors, Kovács-Vajna [1] adopted city block (Manhattan) distance and Bazen et al. [5] used Euclidean distance. The literature on image-based minutia descriptors is very sparse. Instead of original fingerprint images, processed images using techniques such as fingerprint normalization, enhancement, and binarization [18], should be used to handle common intraclass variations in brightness, contrast, and ridge thickness. There also exists other options for distance measures, such as inner product and normalized inner product (cosine distance).

B. Texture-based

Tico and Kuosmanen [2] proposed an orientation-based minutia descriptor, which is composed of local ridge orientation at a set of sampling points defined in the local coordinate system. Orientation-based descriptor was extended to texture-based descriptor by adding ridge frequency information in [3]. Other configurations of sampling points have also been used to construct orientation-based descriptors in [6], [7].

Park et al. [19] employed SIFT descriptor [16] for fingerprint matching. However, gradient information captured in SIFT descriptor is not as stable as ridge orientation in fingerprint-like patterns, since gradient magnitude depends on image contrast and gradient direction changes abruptly from ridge to valley.

C. Minutiae-based

Minutiae-based descriptors have been used by many researchers to increase the distinctiveness of the central minutia. Minutiae-based descriptors can be further classified into two types: nearest neighbor-based and fixed radius-based [20].

Nearest neighbor-based representation is used in [10], [11], [12], [13], [14]. Hrechak and McHugh [10] defined an eight-dimensional feature vector with each dimension representing the number of certain type of minutiae in the neighborhood of the central minutia. This technique is not practical due to the difficulty of reliably discriminating various types of minutiae. Wahab et al. [11], Jiang and Yau [12], Jea and Govindaraju [13] sorted neighboring minutiae with respect to distance or angle in the local polar coordinate system, and the feature vectors consist of relationships between the first m neighboring minutiae and the central minutia. Asai et al. [14] divided the surrounding region of a minutia into four sectors and selected the nearest minutia in each sector.

Fixed radius-based representations used in [9], [8], [3] consist of all minutiae in the neighborhood of the central minutia. The similarity between two minutiae sets is computed by some local minutiae matching algorithm. These minutiae set based descriptors differ in the way how intraclass variations are handled and the similarity is computed. Different from most fixed radius-based descriptor, a new fixed radius-based descriptor in [21], Minutia Cylinder-Code (MCC), represents all neighboring minutiae as a fixed-length vector.

III. Implementation Details

A. Image-based

Image-based descriptor is composed of pixel values in a circular region of radius r centered at the central minutia and oriented along the minutia direction. There are three possible sources for obtaining pixel values: (i) original image, (ii) enhanced image, or (iii) binarized image. To handle brightness variations, pixel values in the original image should be adjusted by subtracting local mean. As to distance measure, cosine distance is adopted for original and enhanced images, and hamming distance is adopted for binarized images.

Since image-based descriptor is sensitive to small disturbance of central minutiae, the circular region of one minutia is rotated and translated to best match the circular region of the other minutia. The range of rotation is $[-12, 12]$ degrees and the interval is three degrees. The range of translation is $(x, y)| - 5 < x < 5, -5 < y < 5$ and the interval is one pixel. The highest similarity under all translations and rotations is used as the similarity between two descriptors.

To deal with occlusion, only those pixels belonging to the foreground of both fingerprints are considered in measuring the distance between descriptors. To avoid unreliable similarity in the case of very serious occlusion (i.e., the proportion of valid pixels is less than 25%), the similarity in such cases is directly set to the minimum value.

An example is given in Fig. 2 to compare different versions of the image-based descriptors. Using grayscale images and Euclidean or city block distance [1], [5], the similarity between mated descriptors (Fig. 2a and b) is lower than that between non-mated descriptors (Fig. 2a and c). But using binarized images and hamming distance, the similarity between mated descriptors is higher than that between non-mated ones. Thus, in the subsequent experiments, we use binarized images to

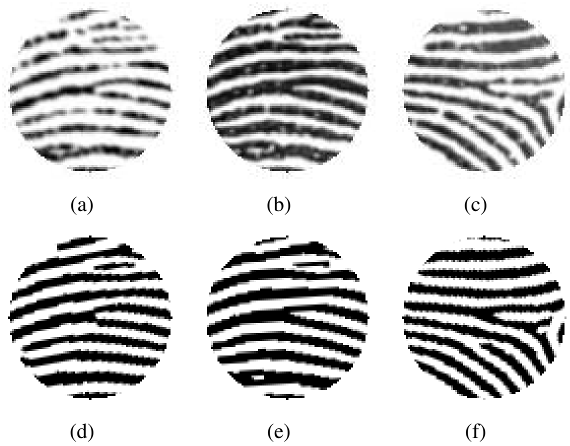


Fig. 2. Ridge thickness variations in different impressions of the same fingerprint. (a) The neighborhood of a minutia in the first impression, (b) corresponding region in the second impression, (c) non-corresponding region in the second impression, (d-f) binarized versions of (a-c).

construct descriptors and hamming distance for distance measure.

B. Texture-based

Orientation-based descriptors consist of local ridge orientation at a set of sampling points in the neighborhood of the central minutia [2], and texture-based descriptors consist of both orientation and frequency at sampling points [3]. These sampling points are distributed on four circles centered at the central minutia. The radius and the number of sampling points of the four circles are (27,10), (45,16), (63,22), (81,28), respectively, as suggested in [2]. Sampling points in the background are deemed as invalid.

Let α and v denote the orientation and period at a sampling point, respectively. The similarity between two descriptors is computed as the mean similarity of all valid corresponding sampling points. The similarity between orientation (s_o), frequency (s_f) and texture (s_t) of two sampling points are computed as follows:

$$s_o = e^{-|norm1(\alpha_1 - \alpha_2)|/(\pi/16)}, \quad (1)$$

$$s_f = e^{-|v_1 - v_2|/3}, and \quad (2)$$

$$s_t = (s_o + s_f)/2, \quad (3)$$

where function $norm1()$ normalizes an angle to $[-\pi/2, \pi/2]$. In the case of very serious occlusion (i.e., the proportion of valid sampling points is less than 25%), the similarity is directly set to 0.

C. Minutiae-based

Minutiae-based descriptors exploit relationships between neighboring minutiae and the central minutia, which include the polar coordinates (ρ, ϕ) and the direction θ of the neighboring minutia in the local coordinate system, and ridge count n between two minutiae. Different descriptors differ in the selection of neighboring minutiae and the similarity measure. Here

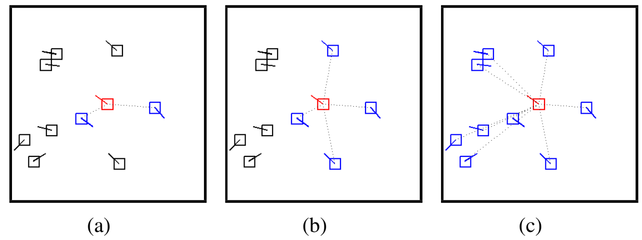


Fig. 3. Neighboring minutiae used in four types of minutiae-based descriptors. (a) Nearest Minutiae, (b) Quadrant Nearest Minutiae, (c) Minutia Set and Minutia Cylinder-Code. Neighboring minutiae used in the descriptor are connected to the central minutia.

we selected four typical minutiae-based descriptors: Nearest Minutiae [12], Quadrant Nearest Minutiae [14], Minutiae Set [3], and Minutia Cylinder-Code (MCC) [21].

Two nearest neighboring minutiae are used in the nearest minutiae descriptor [12]. The descriptor is represented as a 10-dimensional feature vector $f = [\rho_1, \phi_1, \theta_1, n_1, t_1, \rho_2, \phi_2, \theta_2, n_2, t_2]$, where t denotes minutia type: termination (1) or bifurcation (2). The similarity between two vectors f_1 and f_2 is computed by: $s_{nm} = 1 - \min(1, w' \cdot Dist(f_1, f_2))$, where w is the weight vector, and the weights of distance, angle, ridge count and minutia type have been empirically selected as 1/100, 1/300, 1/30, and 1/20, respectively; function $Dist()$ computes the absolute value of the difference between corresponding components of f_1 and f_2.

The nearest neighboring minutia in each of the four quadrants, which is defined according to the local minutia coordinate system, is used in the quadrant minutiae descriptor [14]. Both the feature vector and similarity formula are similar to those of the nearest minutiae descriptor except that four neighboring minutiae are used.

All neighboring minutiae whose distance from the central minutia is less than 80 pixels are used in the minutiae set descriptor [3]. A local minutiae matching algorithm is employed to classify each neighboring minutia into one of the three categories: matched, non-matched with penalty, and non-matched without penalty. Let m_1 and m_2 denote the number of matched neighboring minutiae, and n_1 and n_2 denote the number of non-matched neighboring minutiae with penalty in two descriptors, respectively. The similarity is computed by:

$$s_m = \frac{m_1 + 1}{m_1 + n_1 + 1} \cdot \frac{m_2 + 1}{m_2 + n_2 + 1}. \quad (4)$$

The Minutia Cylinder-Code of a minutia records the relationship between the central minutiae and the neighboring minutiae using a cylinder [21]. The value of each cell in the cylinder is equal to the contribution of neighboring minutiae. The number of cells along the cylinder diameter is 16 and the other parameters are the same as the original paper.

IV. Experimental Results

In this section, we first describe the dataset, feature extraction algorithm and ground-truth data. Then we present the evaluation method. Finally, experimental results are analyzed.

A. Dataset

In our experiments, fingerprints in FVC2002 DB1_A were used, which are plain fingerprints captured by an optical sensor. To study the performance of descriptors in detail, we choose four subsets of fingerprint pairs: 1) good quality, 2) poor quality, 3) small common region, and 4) large plastic distortion. Each subset contains 10 pairs of mated fingerprints. See Fig. 4 for an example in each subset.

For a grayscale fingerprint image, the algorithm proposed by Hong et al. [22] was used to produce a skeleton image. From the skeleton image, minutiae are detected and ridges are extracted by tracing. False minutiae are removed using the rules described in [23]. Each minutia has five features: x and y coordinate, direction, type (termination or bifurcation), and reliability (0 or 1). The ridge counts between minutiae are estimated based on thinned images.

To obtain ground-truth matching minutiae pairs, which are needed in descriptor evaluation, a minutiae matching algorithm is used to find matching minutiae pairs, which are then manually corrected.

B. Evaluation criterion

We use precision versus recall as the evaluation criterion of descriptors. Given a pair of mated fingerprints and the ground-truth minutiae pairs, similarities of descriptors of all minutiae pairs are computed. Minutiae pairs whose similarities are greater than threshold t are regarded as matching minutiae pairs. By comparing the matching minutiae pairs with the ground-truth minutiae pairs, we count the number of correct matching minutiae pairs and the number of false matching minutiae pairs. Precision is the proportion of correct matching minutiae pairs with respect to the number of all matching minutiae pairs. Recall is the proportion of correct matching minutiae pairs with respect to the number of the ground-truth minutiae pairs. By changing the value of t, we obtain a set of precisions and recalls, which are referred to as precision vector and recall vector. The above procedure is performed for N pairs of fingerprints to obtain N precision vectors and N recall vectors. The averages of N precision vectors and recall vectors are used to plot the precision versus recall curve.

C. Performance

The precision versus recall curves on the four subsets are given in Fig. 5. From this figure, the following conclusions can be made:

1) Performances of all descriptors in the three difficult situations are much poorer than that in the easy situation.
2) The ranks of descriptors on different subsets are not exactly the same. This indicates that no single descriptor is the best in all situations.
3) In the situation where the common area is small, texture-based descriptor gives the best result. Minutiae based descriptors are inferior because the available minutia information is very limited in this situation. Texture-based descriptor is better than the orientation-based one in all cases, indicating ridge frequency information does contain complementary information to the ridge orientation.
4) Except for the small common region case, MCC is the most accurate descriptor.
5) Minutiae Set descriptor has a good performance in the high recall region of the curves, especially in the case of plastic distortion, thanks to its flexibility in handling distortion.
6) Although recording most of information in fingerprints, image-based descriptor provides an average performance and it is very sensitive to plastic distortion.
7) Nearest minutiae and Quadrant nearest minutiae are worse than other descriptors in most cases due to their sensitivity to missed and spurious minutiae.

V. Summary and Future Work

In this paper, seven minutia descriptors of three different types, namely image-based, texture-based, and minutiae-based, are evaluated in the context of fingerprint verification. Four subsets of fingerprint pairs from FVC2002 DB1_A are used to in different situations including good quality, poor quality, small common region, and large plastic distortion. MCC was found to perform the best in three subsets and the texture-based descriptor is the most accurate one in the subset of small common region.

However, we can not draw a general conclusion that which type of descriptor or which one of minutiae-based descriptors is the best or which one should be used for every fingerprint matching system. The selection of descriptors depends on applications, characteristics of images, performance of feature extraction, and requirement of global matching algorithms. The most accurate descriptor may not be the best choice for the scenario where the resource of computation and storage is very limited.

We plan to make the evaluation experiment more comprehensive by using additional databases, such as fingerprint databases of various types (plain, rolled, and latent) and palmprint databases. We also plan to evaluate the descriptors in terms of global matching accuracy. Currently, the algorithms for constructing and comparing descriptors are implemented in Matlab or C++. To make a fair comparison of computational costs of different descriptors, it is necessary to implement all the descriptors in C++.

Acknowledgment

This work was supported by the National Natural Science Foundation of China under Grants 61020106004, 60875017, 61005023, and 61021063.

References

[1] Z. Kovacs Vajna, “A Fingerprint Verification System Based on Triangular Matching and Dynamic Time Warping,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 11, pp. 1266–1276, 2000.

[2] M. Tico and P. Kuosmanen, “Fingerprint Matching Using an Orientation-based Minutia Descriptor,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 8, pp. 1009–1014, 2003.

[3] J. Feng, “Combining Minutiae Descriptors for Fingerprint Matching,” *Pattern Recognition*, vol. 41, no. 1, pp. 342–352, 2008.

Fig. 4. Examples of four sets of fingerprint pairs: (a) good quality, (b) poor quality, (c) small common area, and (d) large plastic distortion.

[4] R. Cappelli, D. Maio, D. Maltoni, J. L. Wayman, and A. K. Jain, "Performance evaluation of fingerprint verification systems," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 28, no. 1, pp. 3–18, 2006.

[5] A. M. Bazen, G. T. B. Verwaaijen, S. H. Gerez, L. P. J. Veelenturf, and B. J. van der Zwaag, "A Correlation-based Fingerprint Verification System," in *Proc. 11th Annual Workshop on Circuits Systems and Signal Processing (ProRISC)*, November 2000, pp. 205–213.

[6] J. Qi and Y. Wang, "A robust fingerprint matching method," *Pattern Recognition*, vol. 38, no. 10, pp. 1665–1671, 2005.

[7] X. Wang, J. Li, and Y. Niu, "Fingerprint matching using orientationcodes and polylines," *Pattern Recognition*, vol. 40, no. 11, pp. 3164–3177, 2007.

[8] X. Chen, J. Tian, and X. Yang, "A New Algorithm for Distorted Fingerprints Matching Based on Normalized Fuzzy Similarity Measure," *IEEE Trans. Image Processing*, vol. 15, no. 3, pp. 767–776, 2006.

[9] N. K. Ratha, R. M. Bolle, V. D. Pandit, and V. Vaish, "Robust fingerprint authentication using local structural similarity," 2000, pp. 29–34.

[10] A. K. Hrechak and J. A. McHugh, "Automated fingerprint recognition using structural matching," *Pattern Recognition*, vol. 23, no. 8, pp. 893–904, 1990.

[11] A. Wahab, S. H. Chin, and E. C. Tan, "Novel approach to automated fingerprint recognition," *IEE Proceedings: Vision, Image and Signal Processing*, vol. 145, no. 3, pp. 160 –166, 1998.

[12] X. Jiang and W. Y. Yau, "Fingerprint Minutiae Matching Based on the Local and Global Structures," in *Proc. 15th Int'l Conf. Pattern Recognition*, 2000, pp. 1038–1041.

[13] T.-Y. Jea and V. Govindaraju, "A Minutia-Based Partial Fingerprint Recognition System," *Pattern Recognition*, vol. 38, no. 10, pp. 1672 – 1684, 2005.

[14] K. Asai, H. Izumisawa, K. Owada, S. Kinoshita, and S. Matsuno, "Method and device for matching fingerprints with precise minutia pairs selected from coarse pairs," US Patent No. 4,646,352, 1987.

[15] K. Mikolajczyk and C. Schmid, "A performance evaluation of local descriptors," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 10, pp. 1615–1630, 2005.

[16] D. Lowe, "Distinctive Image Features From Scale-Invariant Keypoints," *International Journal of Computer Vision*, vol. 20, pp. 91–110, 2003.

[17] S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognition using shape contexts," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 4, pp. 509–522, 2002.

[18] A. K. Jain, L. Hong, and R. M. Bolle, "On-line Fingerprint Verification," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 19, no. 4, pp. 302–314, 1997.

[19] U. Park, S. Pankanti, and A. K. Jain, "Fingerprint verification using SIFT features," 2008, p. 69440K.

[20] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition (2nd Edition)*. Springer, 2009.

[21] R. Cappelli, M. Ferrara, and D. Maltoni, "Minutia cylinder-code: A new representation and matching technique for fingerprint recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 32, no. 12, pp. 2128–2141, 2010.

[22] L. Hong, Y. Wan, and A. K. Jain, "Fingerprint Image Enhancement: Algorithm and Performance Evaluation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, 1998.

[23] Z. Bian, D. Zhang, and W. Shu, "Knowledge-based fingerprint post-processing," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 16, no. 1, pp. 53–67, 2002.

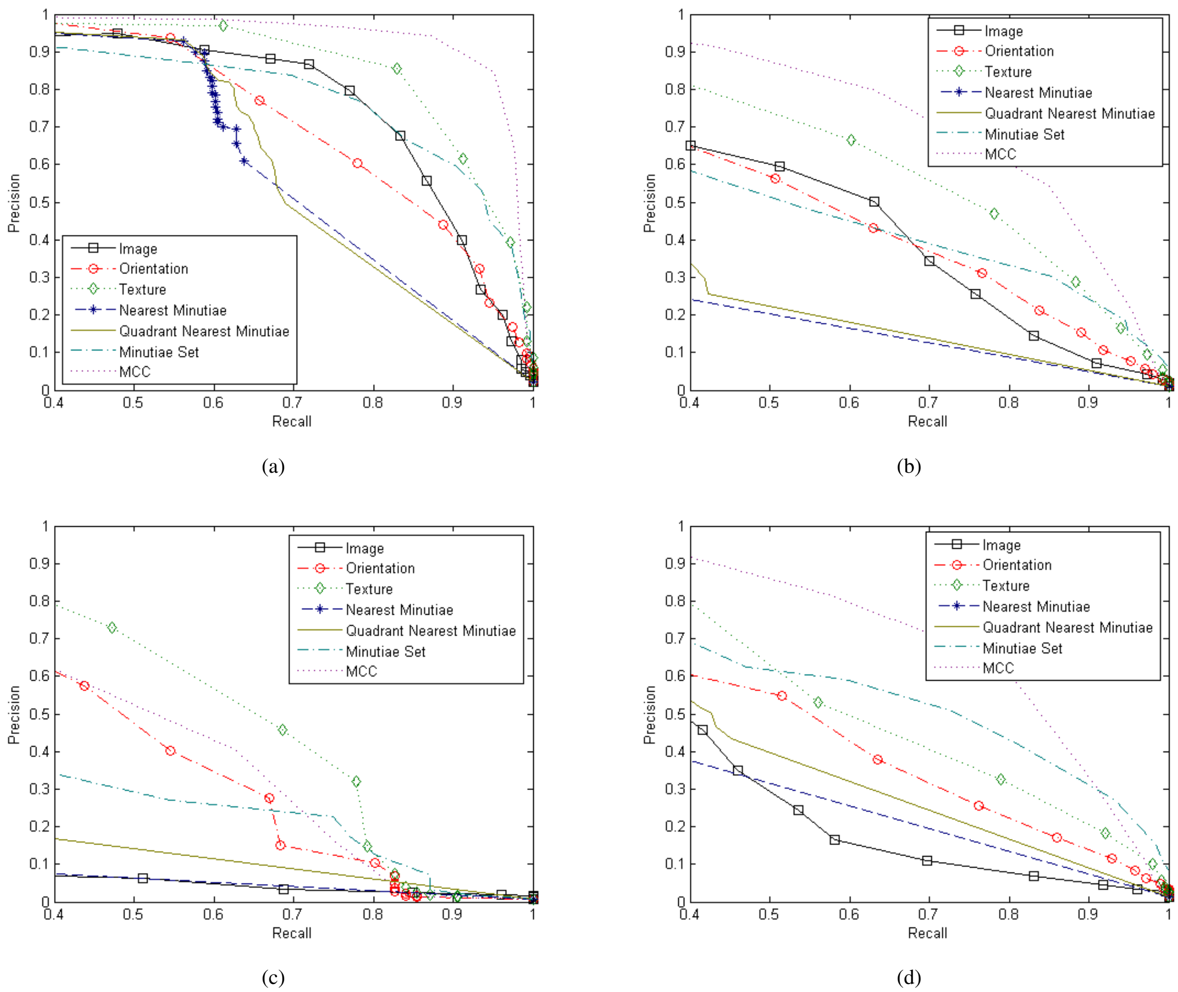


Fig. 5. Performance of descriptors on four subsets of fingerprint pairs from FVC2002 DB1_A: (a) good quality, (b) poor quality, (c) small common area, and (d) large plastic distortion.