Fingerprint Retrieval for Identification

Xudong Jiang, *Senior Member, IEEE*, Manhua Liu, and Alex C. Kot, *Fellow, IEEE*

***Abstract*—This paper presents a front-end filtering algorithm for fingerprint identification, which uses orientation field and dominant ridge distance as retrieval features. We propose a new distance measure that better quantifies the similarity evaluation between two orientation fields than the conventional Euclidean and Manhattan distance measures. Furthermore, fingerprints in the data base are clustered to facilitate a fast retrieval process that avoids exhaustive comparisons of an input fingerprint with all fingerprints in the data base. This makes the proposed approach applicable to large databases. Experimental results on the National Institute of Standards and Technology data base-4 show consistent better retrieval performance of the proposed approach compared to other continuous and exclusive fingerprint classification methods as well as minutia-based indexing schemes.**

***Index Terms*—Distance measure, fingerprint classification, fingerprint identification, fingerprint retrieval.**

I. Introduction

FINGERPRINTING is one of the most widely used biometric features to recognize a person. Fingerprint verification that compares an input fingerprint with only one template of the claimed identity was extensively studied and promising results were reported. However, fingerprint identification, which requires matching an input fingerprint with all fingerprints in a data base, is still a challenging research problem. The extension of the one to one matching of a verification system to the one to N matching of an identification system on a data base of N fingerprints increases the possibility of the false positive matching. Comparing he verification performance, both the accuracy and the speed may decrease significantly if a verification algorithm is simply extended to solve an identification problem. The accuracy deterioration could be very serious for large-scale identification systems as it is proportional to the number of fingerprints in the data base [1]. This problem can be alleviated by reducing the search space of the exact matching. Fingerprint classification, indexing, or retrieval techniques facilitate the reduction of the search space for identification.

Numerous fingerprint classification approaches [2]–[9], called exclusive classification in the literature, focus on the human predefined Henry classes. Although Henry classes have some advantages, such as human-interpretable and a rigid segmentation of a data base, most automated fingerprint classification systems are able to classify fingerprints into only four or five classes. Moreover, fingerprints are not evenly distributed in these classes. The natural proportions of fingerprints in these five classes estimated on 222 million fingerprints [10] are 3.7, 2.9, 33.8, 31.7, and 27.9%. This greatly limits the effectiveness of applying such a classification scheme into the identification system. On average, we still need to match an input fingerprint with about 29.48% of fingerprints in the data base after the exclusive classification is applied. Therefore, the exclusive classification cannot effectively narrow down the search space. Another problem is that there are many ambiguous fingerprints, whose class membership cannot be exclusively stated despite the small number of human-interpretable classes.

In general, the classification of fingerprints into human-interpretable classes is not required for an automated system. Some techniques were proposed to index fingerprints using minutia points [11], [12]. An advantage of these approaches is that they can classify fingerprints into more classes than the exclusive classification as they exploit more discriminating features, fingerprint minutiae. However, these indexing approaches construct a redundant representation of fingerprint because minutia points are used in most automated fingerprint matching algorithms. Information contained in the feature for the indexing is therefore highly correlated with or just a subset of that used in the subsequent finer matching. As a result, these approaches can barely alleviate the accuracy deterioration caused by the extension of the one-to-one matching to the one-to-N matching although they can speed up the identification process.

As an orientation field is less correlated with the minutiae used in the finer matching [13], the "continuous" classification [14]–[16] based on the orientation field is expected to alleviate both the accuracy and the speed deterioration of an identification system. This technique extracts an orientation feature vector from the fingerprint image. A portion of fingerprints in the data base is retrieved by comparing an input feature vector with all vectors in the data base and selecting those that are close to it. The continuous classification technique circumvents the difficult exclusive classification problem of very limited classification efficiency (small number of classes). However, this technique needs to compare the input vector with those of all fingerprints in the data base. Although the comparison is much faster than the finer matching, it could be time consuming for a large data base. Moreover, the retrieval performances of the existing approaches are still not very attractive even though efforts of combining different features and techniques showed some improvements [17], [18]. Hence, further investigation on the fingerprint retrieval is still of great interest to researchers in the field of fingerprint identification.

This paper proposes a fingerprint retrieval framework based on the continuous classification scheme. Besides orientation field as the main retrieval feature, the dominant ridge distance that has very low correlation with minutiae is introduced as an auxiliary feature. A new distance measure is proposed in this work that better quantifies the similarity evaluation between

Manuscript received April 18, 2005; revised August 4, 2006. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Jerry D. Gibson.

The authors are with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798 (e-mail: exdjiang@ntu.edu.sg; pg05080538@ntu.edu.sg; eackot@ntu.edu.sg).

Digital Object Identifier 10.1109/TIFS.2006.885021

Fig. 1. Examples of orientation field, reference point, and direction superimposed on the fingerprint, where the short (thicker/thinner) line represents the local orientation (included in/excluded from the feature vector) and the small square and arrow for the reference point and direction, respectively.

two orientation fields than the conventional Euclidean and Manhattan distance measures. In addition, a variable search tolerance is introduced for more efficient retrieval. Furthermore, we propose to partition the data base into clusters to avoid the exhaustive comparisons. This makes the proposed method applicable to large databases and comparable to the widely studied exclusive classification in terms of the retrieval speed. Experiments and comparisons with other approaches on the National Institute of Standards and Technology data base-4 show the feasibility of the proposed approaches.

II. Feature Extraction

To alleviate the accuracy deterioration caused by the 1 to N matching in fingerprint identification systems, we exploit orientation field and ridge distance as retrieval features, which have low correlation with minutiae that are often used in fingerprint matching. As most images contain both the fingerprint foreground and the noisy background, a segmentation algorithm is applied to separate them. A reference point is detected and its location and direction are computed to produce a feature vector invariant to the translation and rotation of the fingerprint.

A. Orientation Field Computation and Segmentation

A fingerprint orientation field consists of local dominant orientations estimated in different local neighborhoods of a fingerprint image. The gradient-based estimation method is widely employed for the orientation field computation [19]–[21]. Our earlier developed two-stage estimation method [22] is employed in this work. The first stage computes the orientation vector and its anisotropy of each small nonoverlapping block by averaging the squared gradients within the block (of size 9×9 in the experiment). The final dominant orientation and its anisotropy are computed in the second stage by averaging the normalized orientation vectors of small blocks weighted by their anisotropy values.

Determining the number of the small blocks $q \times q$ in the second stage of average is crucial to achieve a robust orientation estimation. Larger q is usually required for a smooth orientation field, especially in noisy areas. A measure similar to the anisotropy is exploited to determine the number q adaptively in [23], [24]. One problem is that this measure cannot differentiate the noisy area from the high curvature area where smaller q should be used. The difference between these two difficult areas is that the estimated anisotropy usually becomes larger with the increase of q in the noisy area while it remains small with increasing q in the high-curvature area for a certain range. Therefore, we increase q from 3 to 7 and determine the optimal value of q adaptively by analyzing not only the anisotropy value but also its variation with q. Fig. 1 shows the estimated orientation fields of three fingerprints.

Most fingerprint images have some blank and heavy noisy areas. If local orientations in these areas are included in the feature vector, its within-finger variance will be greatly increased. A reliable feature vector should exclude these corrupted orientations. Therefore, fingerprint segmentation is necessary for the feature selection. The fingerprint segmentation algorithm in [25] is applied that uses three features: block mean gray value, variance of gray values, and anisotropy or coherence. A linear classifier is trained for the segmentation and a morphological filter is employed in the postprocessing to obtain compact fore and background areas.

B. Orientation Feature Vector Construction

Translation and rotation usually exist in different fingerprints originating from the same finger. The orientation feature vector should be invariant to such transformation among different fingerprints. One solution is to align the fingerprints using some landmark points. Core and delta points usually serve as two landmark points for the alignment. As a delta point is often out of the captured fingerprint, the location and direction of the core point are more reliable for the alignment purpose. The core point was exploited for the translational alignment of fingerprints in [3], [4], and [14]. In fact, any point can serve as an alignment reference so long as it can be consistently detected.

As no core point exists in plain arch fingerprints, a reference point defined by the minimal orientation coherence is detected by analyzing the orientation coherence of varying scales [26]. Spurious reference points caused by noise are eliminated in the larger scale and the accurate location of the true reference point is determined in the finer scale. A reference direction is determined by finding the radial direction from the reference point that is most parallel to the local ridge orientations along the radial [27]. For plain arch fingerprints, two such directions will be found and the average of them serves as our reference direction. When multiple points are detected, the point whose direction is toward the southernmost point is selected as our reference point. This approach can determine a reference point and its direction for all types of fingerprints. Some examples of the detected reference point and its direction are shown in Fig. 1.

Let $\theta_{x,y}, -\pi/2 < \theta_{x,y} \leq \pi/2$, be the local orientation with x- and y-coordinates in the orientation field. If (x_r, y_r) and $\theta_r, -\pi < \theta_r \leq \pi$, are the reference location and direction, respectively, the coordinates of the aligned orientation field, represented by a complex variable $m + jn$, are calculated by

$$m + jn = [x - x_r + j(y - y_r)]e^{-j\theta_r}. \tag{1}$$

Due to the periodicity and discontinuity of the orientation $\theta_{m,n}$ at $\pm\pi/2$ and the direction θ_r at $\pm\pi$, the proper computation of the aligned local orientation should be

$$\hat{\theta}_{m,n} = \begin{cases} \Delta\theta, & \text{if } -\pi/2 < \Delta\theta \leq \pi/2, \\ \Delta\theta - \pi, & \text{if } \Delta\theta > \pi/2, \\ \Delta\theta + \pi, & \text{if } \Delta\theta \leq -\pi/2 \end{cases} \tag{2}$$

where $\Delta\theta = \theta_{m,n} - \theta_r$. Obviously, $-\pi/2 < \hat{\theta}_{m,n} \leq \pi/2$.

Our orientation feature vector $O = \{o_k, k = 1, 2, \ldots, K\}$ is constructed by concatenating the aligned local orientations within a circle of radius R, excluding the one nearest to the reference point, that is

$$O = \{\forall\hat{\theta}_{m,n} \,|\, (m^2 + n^2 < R^2) \wedge ((m,n) \neq (0,0))\}. \tag{3}$$

For the application to the NIST data base-4, local orientation is computed every 27 pixels along the horizontal and vertical axes and $R = 8$ is selected. The constructed orientation feature vector has $K = 192$ elements, which covers the fingerprint image of size $27[2(8-1)+1] \times 27[2(8-1)+1] = 405 \times 405$. The dimensionality of the feature vector is equal to that of "FingerCodes" [3].

The orientation feature vector covers most of the fingerprint if the reference point is located at the center of the image. In some cases, however, it covers only a part of the fingerprint and a substantial number of elements are from a noisy background or out of the image region due to the unfavorable position of the reference point. The segmentation algorithm is therefore used to label the valid $(s_k = 1)$ and invalid $(s_k = 0)$ elements of the feature vector.

Instead of the orientation angle o_k, some approaches [4], [14], [15] employ the unit orientation vector $[\cos(2o_k), \sin(2o_k)]$ as the classification feature. While this representation is necessary to facilitate some feature transform and weighting, it doubles the size of the feature vector. As we will see later, the unit orientation vector representation has a very similar function to angle representation if Euclidean distance is applied to compare two orientation fields. Therefore, in this work, we choose the angle representation to reduce the size of feature vector by half.

Some approaches [4], [5], [14], [15] exploit the Karhunen–Loeve (KL) transformation (principle component analysis) or multispace KL to project the higher dimensional orientation feature vector onto a lower dimensional one. In the practical applications, feature vectors of different fingerprints may have quite different valid and invalid elements due to the translation, rotation, and unfavorable reference point locations. This may negatively affect the reliability of the covariance matrix and the obtained transformation matrix. Furthermore, the transformation of the feature vector into the eigenspace combines all elements of the feature vector in the original space. This may result in large error for feature vectors that have a substantial number of invalid elements. Therefore, we do not apply such a transformation technique in this work.

It was concluded in [4] that the performance of exclusive fingerprint classification was improved by replacing the uniform spacing orientation field with a nonuniform one throughout the fingerprint image. The nonuniform spacing concentrates orientation measurements more densely in the important central area of the image than in the less important outer regions. "FingerCodes" [3] also applies a nonuniform partition of fingerprint. It was further accomplished in [4] that performance improvement similar to that of nonuniform spacing was achieved by using regional weights. Therefore, we adopt the uniform spacing orientation field the same as that used in the fingerprint image enhancement and minutia extraction to avoid the double computation of the orientation field. Later, we shall present our regional weighting scheme that is different from those in [4] and [16] together with the distance measure.

C. Dominant Ridge Distance Computation

Fingerprint local ridge distance is defined as the distance between the center points of two adjacent ridges along a line perpendicular to the local ridge orientation. It is another important intrinsic property of fingerprint as its inverse represents the ridge density or ridge frequency. The local ridge distance was used for fingerprint image enhancement [19]. For fingerprints scanned at 500 dpi, the local ridge distance varies from 3 to 25 pixels [19]. Obviously, it has discrimination capability, is independent of the orientation field, and has very low correlation with minutia. Therefore, the ridge distance is an appropriate feature for fingerprint retrieval that does not bring redundant representation of fingerprinting in the identification system. The fingerprint local ridge distance map $\{\lambda_{x,y}\}$ can be estimated by one of the available approaches [19], [28], [29] in the literature.

However, the local ridge distance of a same finger varies due to the different manners that an elastic finger presses on a plane sensor. Moreover, noise and image deterioration result in large estimation error. Our experiments show that the estimated local ridge distance is much less stable than the local orientation. It seems not viable to construct a high dimensional feature vector using local ridge distances for retrieval. Nevertheless, the average ridge distance over the fingerprint foreground shows a stable yet discriminative feature. The average within-finger variance of the average ridge distance over NIST data base-4 is 0.033 and its between-finger variance is 0.494, which lead to a discriminant value of $0.494/0.033 = 14.97$. We further find that some local ridge distances largely deviate from the mean due to the existence of minutia, ridge break, bad ridge separation, and other heavy noise. These outliers result in large variation of the average distance. We therefore define a dominant ridge distance λ_D as the second mean over the local ridge distances within a bin centered at the first mean over the fingerprint foreground $\mathcal{F}$ by

$$\lambda_D = \text{mean}\{\forall\lambda_{x,y} \,|\, ((x,y) \in \mathcal{F}) \wedge (|\lambda_{x,y} - \lambda_M| < b)\} \tag{4}$$

where

$$\lambda_M = \text{mean}\{\forall \lambda_{x,y} \,|\, (x,y) \in \mathcal{F}\}. \tag{5}$$

With a proper choice of threshold b, outliers of the local ridge distance will be excluded from the computation of the dominant ridge distance λ_D. The average within-finger variance of the dominant ridge distance with $b = 2$ over the NIST data base-4 is 0.028 and its between-finger variance is 0.665, which lead to a discriminant value of 0.665/0.028=23.75. It is visibly higher than 14.97 of the average ridge distance. The dominant ridge distance λ_D computed by (4) and (5) is used in this work as an auxiliary scalar feature for fingerprint retrieval.

III. Distance Measure

Euclidean and Manhattan distance measures are widely used in computing the distance of two vectors. As the feature vector $O^p = \{o_k^p, k = 1, 2, \ldots, K\}$ of a fingerprint p consists of orientation angles that are periodic, have a discontinuity at $\pm\pi/2$, and could be valid ($s_k^p = 1$) or invalid ($s_k^p = 0$), the Euclidean $d_E(O^p, O^q)$ and Manhattan $d_M(O^p, O^q)$ distances of two fingerprints p, q are computed by

$$d_E(O^p, O^q) = \sqrt{\frac{1}{\sum_{k=1}^{K} s_k^p s_k^q} \sum_{k=1}^{K} s_k^p s_k^q \left(\Delta_k^{p,q}\right)^2} \tag{6}$$

$$d_M(O^p, O^q) = \frac{1}{\sum_{k=1}^{K} s_k^p s_k^q} \sum_{k=1}^{K} s_k^p s_k^q \Delta_k^{p,q} \tag{7}$$

where

$$\Delta_k^{p,q} = \min\left(|o_k^p - o_k^q|, \pi - |o_k^p - o_k^q|\right). \tag{8}$$

Some approaches [4], [14], [15] employ the unit orientation vector $[\cos(2o_k), \sin(2o_k)]$ representation. From the trigonometry, we can easily have

$$\begin{aligned}(\cos 2o_k^p - \cos 2o_k^q)^2 &+ (\sin 2o_k^p - \sin 2o_k^q)^2 \\ &= 4\sin^2(o_k^p - o_k^q) = \left(2\sin\Delta_k^{p,q}\right)^2. \end{aligned} \tag{9}$$

Obviously, if the Euclidean distance is applied, this unit vector representation that doubles the feature vector size maps $0 \leq \Delta_k^{p,q} \leq \pi/2$ in (6) to $0 \leq 2\sin(\Delta_k^{p,q}) \leq 2$, which produces very similar distance to that of angle o_k.

The problem of the Euclidean and Manhattan distance measures is that a small amount of rotation between two aligned fingerprints of the same finger contributes a small constant amount to $\Delta_k^{p,q}$ for all k. This small difference may result in a large distance as it exists in all vector elements. To solve this problem, we propose a new distance measure for two orientation vectors as

$$d_C(O^p, O^q) = 1 - \frac{\left|\sum_{k=1}^{K} v_k e^{j2(o_k^p - o_k^q)}\right|}{\sum_{k=1}^{K} v_k} \tag{10}$$

where $v_k = s_k^p s_k^q, j = \sqrt{-1}$ and $|z|$ compute the magnitude of the complex variable z.

Instead of averaging the absolute or squared difference over the valid orientations with (6) or (7), the proposed distance measure (10) averages the unit vector whose phase is the doubled orientation difference. It measures the inconsistency of the orientation differences among the valid elements of two feature vectors. We can see that the proposed distance $d_C(O^p, O^q)$ has the minimum of zero for a constant orientation difference $o_k^p - o_k^q$ (constant to k) and it reaches the maximum of one when the orientation differences are uniformly distributed in a range of π or its multiples. Let a and b be two scalars and I be a unit vector of the same dimensionality as O. It is easy to verify that the proposed distance measure satisfies

$$d_C(O^p + aI, O^q + bI) = d_C(O^p, O^q) \tag{11}$$

because

$$\begin{aligned} &\left|\sum_{k=1}^{K} v_k e^{j2(o_k^p + a - o_k^q - b)}\right| \\ &\quad = \left|e^{j2(a-b)}\right| \left|\sum_{k=1}^{K} v_k e^{j2(o_k^p - o_k^q)}\right| \\ &\quad = \left|\sum_{k=1}^{K} v_k e^{j2(o_k^p - o_k^q)}\right|. \end{aligned} \tag{12}$$

This means that a constant amount of orientation difference caused by a slight rotation between two aligned fingerprints due to a small estimation error of the reference direction has no effect on the proposed distance measure (10). Another merit of the proposed distance measure is that we need not subtract the reference direction from the original orientation field to construct the orientation feature vector (i.e., (2) is not necessary and we can use $\theta_{m,n}$ instead of $\hat{\theta}_{m,n}$ in the feature vector construction (3)).

In [16], regional weights were used to attenuate the orientations near the border and strengthen those in the irregular regions by applying a Gaussian-like function. We find that the discriminative power of a local orientation is not simply decreased with the distance increase of its location from the singular points. As the entropy of a random variable measures its uncertainty, we propose to weigh a local orientation by its entropy estimated by

$$w_k = -\frac{\sum_{l=1}^{L} p(o_k \in B_l) \log p(o_k \in B_l)}{\log(L)} \tag{13}$$

where L is the number of bins B_l used to partition the orientation range of $(-\pi/2, \pi/2]$ and $p(o_k \in B_l)$ is the occurrence frequency of fingerprints whose local orientations o_k fall in the bin B_l. Note that $p(o_k \in B_l) \log p(o_k \in B_l)$ is set to zero if $p(o_k \in B_l) = 0$ in (13).

The weight w_k has the minimum of zero if the local orientations o_k of all fingerprints fall in the same bin. It reaches to the maximum of one if o_k are evenly distributed over all bins. The left and right images of Fig. 2 show the regional weights computed by (13) using the first instances of all fingerprints in the NIST data base-4 and 1204 fingerprints selected according to the natural distribution, respectively. We see that the fingerprint region below the reference point is significantly more discriminative than the region above that, which is expected. The bright

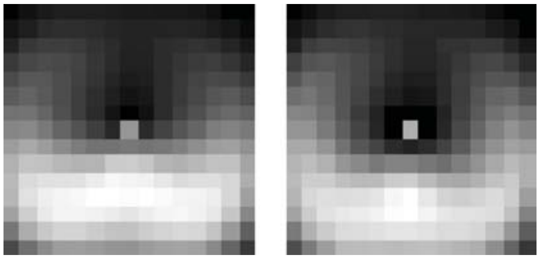

Fig. 2. Gray level representation of the regional weights computed by the entropy estimates on the first instances of (left) NIST data base-4 and (right) 1204 fingerprints selected according to the natural distribution.

center point is due to the unstable orientation of the highest curvature block, which is excluded from the feature vector.

Due to the periodicity and discontinuity of the orientation, we can neither weight the orientation nor its difference directly. Our proposed distance measure with the incorporation of the regional weights is defined by

$$d_W(O^p, O^q) = 1 - \frac{\left|\sum_{k=1}^{K} w_k v_k e^{j2(o_k^p - o_k^q)}\right|}{\sum_{k=1}^{K} w_k v_k}. \tag{14}$$

Similar to the property (11), we have

$$d_W(O^p + aI, O^q + bI) = d_W(O^p, O^q). \tag{15}$$

Let $\alpha_k = w_k v_k$ and $\delta_k^{pq} = 2(o_k^p - o_k^q)$, the proposed distance (14) can be computed by

$$d_W(O^p, O^q) = 1 - \frac{\sqrt{\left(\sum_k \alpha_k \cos \delta_k^{pq}\right)^2 + \left(\sum_k \alpha_k \sin \delta_k^{pq}\right)^2}}{\sum_k \alpha_k}. \tag{16}$$

IV. Retrieval and Data-Base Clustering

In this work, retrieval is defined as: given an input fingerprint, filter out a subset of candidate fingerprints for the finer matching by coarsely searching the data base. If one of the retrieved candidates originates from the same finger as the input, the retrieval is successful for this input fingerprint; otherwise, it is a failure. Therefore, the retrieval accuracy/error is calculated by the percentage of the input fingerprints with retrieval success/failure. As retrieval is to reduce the number of finer matchings for identification, the average percentage of the retrieved fingerprints from the data base over all input fingerprints represents the retrieval efficiency. The performance of a retrieval technique is measured by its accuracy and efficiency. The continuous classification retrieves fingerprints in the data base whose features fall in a neighborhood centered at the input. It usually provides better performance and can balance the efficiency and accuracy more easily than the exclusive classification.

However, the continuous retrieval is required to compare the input feature vector with those of all fingerprints in the data base. This results in substantial longer retrieval time than the exclusive classification. To reduce the time consumption of retrieval, we propose to partition the data base into clusters. The number of clusters is much smaller than the number of fingerprints in the data base. We only need to compare the input feature vector with the cluster prototypes and retrieve fingerprints of one or few clusters. This integrates merits of continuous and exclusive classification in the retrieval. We shall discuss the clustering-based retrieval after introducing our continuous retrieval approach.

A. Continuous Retrieval

Our retrieval features consist of a 1-D dominant ridge distance λ_D and a 192-D orientation vector. As the scalar λ_D is independent of the orientation feature, we sort the fingerprints in the data base according to λ_D. In the online retrieval, we first narrow the search space by selecting a subset of fingerprints whose dominant ridge distances are within a bin (of width 2 pixels in our experiments) centered at the input dominant ridge distance. The 192-D orientation vector is then used to search the candidate fingerprints in the subset of the data base.

Fingerprints in the subset will be retrieved if the distances (16) between their orientation vectors O^p and the input orientation vector O^q are less than a threshold r_n^q

$$d_W(O^p, O^q) < r_n^q \tag{17}$$

where r_n^q represents the retrieval threshold of input fingerprint q that results in n fingerprints retrieved. The retrieval accuracy and efficiency can be adjusted by changing the threshold r_n^q. In an identification system, the retrieval and matching can be integrated so that the retrieval threshold increases from a small value until the input fingerprint is matched with the retrieved template by a matching algorithm. The threshold can increase by a fixed step or based on a fixed number of newly retrieved fingerprints [14], [30]. The incorporation of the fingerprint matching in the retrieval may greatly increase the retrieval performance if a good matching algorithm is applied.

Without applying the matching algorithm, we can only set the retrieval threshold a constant $r_n^q = c$ or some value that results in retrieving a constant portion of data base $r_n^q \,|\, (n = cN)$ for all input fingerprints. N is the total number of fingerprints in the data base and c is determined by a given efficiency or accuracy target. Our experiments show that the variable threshold $r_n^q \,|\, (n = cN)$ leads to a better retrieval performance than the constant one $r_n^q = c$ at a price of longer retrieval time caused by sorting the distances. To avoid the time-consuming data-base sorting, we propose to vary the threshold only by the nearest few fingerprints in the data base. If an input fingerprint has smaller distance from its nearest few fingerprints in the data base, the probability that one of them is the right candidate is higher than the case of larger distance. It is very likely that the former case needs a smaller retrieval threshold than the latter. Therefore, we set the retrieval threshold as

$$r_n^q = r_{bN}^q + c \tag{18}$$

where $b(1/N \le b < 1)$ is a small constant. In our experiments, b is simply fixed to the minimal value $1/N$ and different values of c are used to test the retrieval accuracies at different efficiencies. Our experiments show that the proposed threshold setting $r_n^q = r_1^q + c$ leads to a better retrieval performance than the constant threshold $r_n^q = c$ and surprisingly even better than the variable threshold $r_n^q \,|\, (n = cN)$.

B. Fast Retrieval by Clustering Data base

One problem of the continuous retrieval is that it requires comparing the input feature with those of all fingerprints in the data base. Although this comparison is much faster than the finer matching, it could be time consuming for large databases. We therefore propose a fast retrieval approach based on data-base clustering. Fingerprints in the data base are clustered using orientation vectors. Each cluster is represented by a prototype. The number of clusters is significantly smaller than that of fingerprints in the data base.

A K-means clustering algorithm [31] is employed to partition the orientation feature space into clusters. The proposed distance measure (16) is used in the K-means algorithm. The number of clusters is first initialized by considering the targets of retrieval speed, accuracy, and efficiency. To alleviate the local minimum problem of the K-means algorithm, we merge small clusters and split large ones after the K-means algorithm converges and restart running it with the modified prototypes. This process needs to be iteratively repeated multiple times to produce better clusters. The final number of clusters could be different from the initial one. In the online retrieval process, an input orientation vector needs only to be compared with the cluster prototypes. A few prototypes closest to the input feature vector are selected. From the selected clusters, we finally retrieve fingerprints whose dominant ridge distances are within a bin centered at the input dominant ridge distance.

Compared to the continuous retrieval, the clustering-based approach greatly reduces the retrieval time consumption at a price of some drop in accuracy or efficiency due to the quantization of the feature space and the number of retrieved fingerprints. To alleviate this performance deterioration, we partition the data base into more clusters than that required by the targeted efficiency and usually retrieve more than one cluster. This is because there are always fingerprints located near the cluster boundaries regardless of how well the clusters are formed. Therefore, this approach is not a strictly exclusive classification since the class is not predefined although each fingerprint is exclusively assigned to only one cluster. Nevertheless, the retrieval speed of this approach is comparable to the exclusive classification as it does not compare an input feature with those of all fingerprints in the data base.

V. Experimental Results and Comparisons

Most published results of exclusive and continuous classifications as well as fingerprint indexing are based on the NIST data base-4. To have a comprehensive comparison, we also test our approach using this data base, which contains 4000 fingerprints with a size of 480×512 pixels with 500-dpi resolution, taken from 2000 different fingers with two instances per finger. This data base is collected for the purpose of testing the exclusive classification so that the five human-predefined classes are of the same occurrence frequency in the data base. The natural distribution of fingerprint in these five classes is, however, significantly different with 3.7% for arch, 2.9% tented arch, 33.8% left loop, 31.7% right loop, and 27.9% whorl, respectively. In order to resemble the real distribution of fingerprinting, we reduce the number of fingerprints of less frequent classes and obtain 1204 pairs of fingerprints from NIST data base-4. This reduced data base, called data set 2, and the original NIST data base-4, are both applied in our experiments. In addition, data bases of fingerprint verification competition (FVC) [32] are also applied in the experiments to test the retrieval performance on the online data base captured under less controlled conditions.

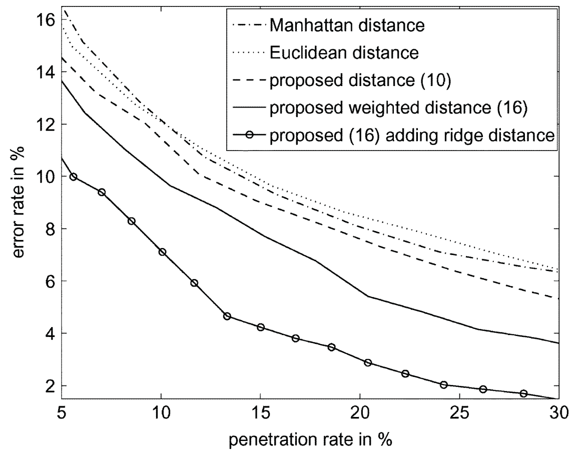

Fig. 3. Comparison of retrieval results with different distance measures and the effect of the inclusion of the dominant ridge distance in the retrieval feature set.

In all experiments, the first fingerprint instances form the data base to be retrieved and the other instances serve as the test input fingerprints. Accuracy and efficiency are two main indications of the retrieval performance. In the experiments, the retrieval error is calculated by the percentage of the input fingerprints whose corresponding ones in the data base fail to be retrieved. The retrieval efficiency is indicated by a so-called penetration rate, which is the average percentage of fingerprints in the data base retrieved over all input fingerprints.

A. Continuous Retrieval on NIST Data Base

The first experiment tests the retrieval performances with different distance measures and the performance gains by the inclusions of the proposed weighting scheme and dominant ridge distance. Data set 2 is applied as it resembles the real fingerprint distribution. Fig. 3 shows the retrieval error rates against the efficiency using Euclidean, Manhattan distances, the proposed distance (10), and weighted distance (16), as well as the proposed approach including the ridge distance feature. While there is little difference between Euclidean and Manhattan distances, the proposed distance (10) consistently improves the retrieval performance. The proposed weighted distance (16) reduces the retrieval error by more than 2% at all penetration rates. Compared to applying the Euclidean or Manhattan distance on the orientation field alone, the proposed approach significantly reduces the retrieval error by about 5% at all penetration rates.

The second experiment tests the retrieval performances with different ways of setting the retrieval threshold. Ridge distance is not used in this experiment as the threshold; r_n^q is only applied to the orientation vector. Fig. 4 shows the retrieval error against the efficiency by using the retrieval thresholds of fixed

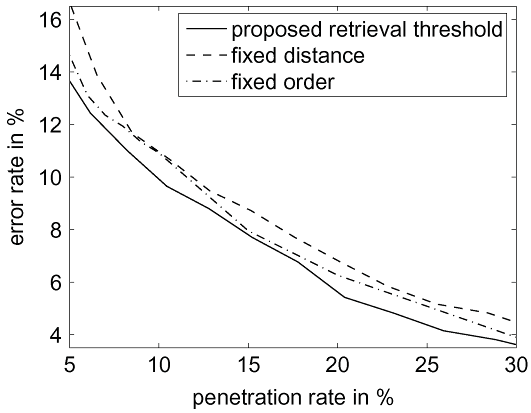

Fig. 4. Comparison of retrieval results with different threshold setting methods.

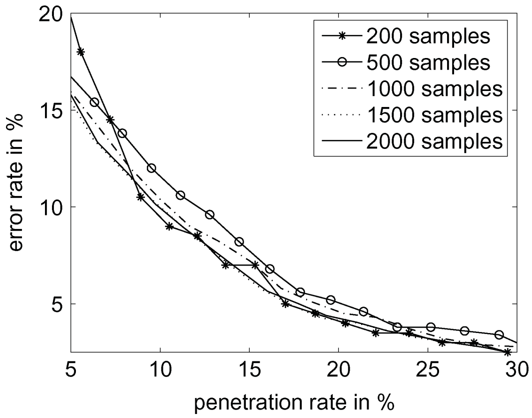

Fig. 5. Comparison of retrieval results with different data-base sizes.

distance ($r_n^q = c$), fixed order ($r_n^q \,|\, (n = cN)$), and the proposed retrieval threshold ($r_1^q + c$). Error rates at different penetration rates are computed by using different values of c, which are constant to all input fingerprints. Note that the better retrieval performance of the fixed order than the fixed distance shown in Fig. 4 is at a price of longer retrieval time caused by sorting the distances of all template fingerprints from the input. In contrast, the proposed threshold setting only needs to find the minimal distance. Fig. 4 shows that the proposed threshold setting $r_n^q = r_1^q + c$ achieves better retrieval performance than the fixed distance $r_n^q = c$ and surprisingly even better than the fixed order $r_n^q \,|\, (n = cN)$.

The third experiment tests the effect of the data-base size on the retrieval performance. It is difficult to derive the retrieval performance on a larger data base from that on a smaller data base. In the absence of general theory, we test the retrieval performances on different subsets picked randomly from the NIST data base-4. Fig. 5 shows the retrieval error against the efficiency for five different data-base sizes. It shows no general trend of the performance deterioration with the increase of data-base size. We further test the error rates at the penetration rate of 10% for 40 different data-base sizes (from 50 to 2000). Fig. 6 shows the retrieval error rate against the data-base size. The oscillation of the curve at small data-base sizes suggests that the performance evaluated on a small data base is unstable. Again, Fig. 6 shows

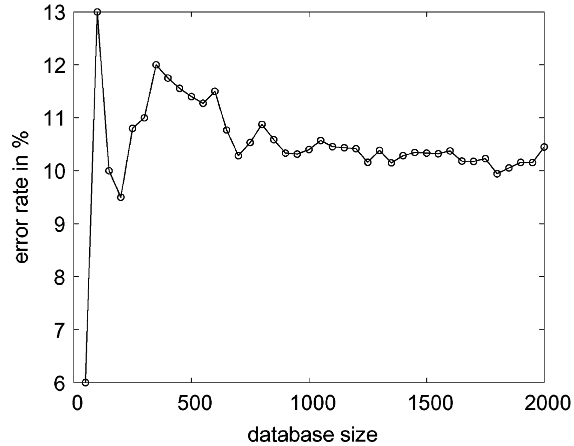

Fig. 6. Retrieval error rate at the penetration rate of about 10% against the number of fingerprints in the data base.

no general trend of the performance deterioration with the increase of data-base size. This is expected because the performance is measured by the percentage of fingerprints in the data base.

Those fingerprint images that are not correctly retrieved are checked manually. The 10% penetration rate leads to an error rate of about 7%. On checking these fingerprints carefully, reference points of 29.72% fingerprints cannot be consistently identified even by the human expert, 56.13% fingerprints show inaccurate or falsely determined reference points, and 14.15% fingerprints show correct reference points but noisy orientation fields. At the retrieval error rate of 4.3%, the percentages of these three error sources change to 44.19, 48.83, and 6.98, respectively. The large penetration rate of 40% leads to a small error rate of 1%. In this case, all errors are caused by the wrongly detected reference points, 60% of which cannot be consistently identified even by the human expert. Fig. 7 show three examples of these images.

To test the computational complexity, the proposed algorithm is implemented by C programming language and was executed under Windows XP Professional O.S. on a Comaq Evo D510CMT (Intel Pentium 4 at 2.26 GHZ) PC. The average search time (of 2000 input fingerprints of the NIST data base-4) for retrieving a subset from the NIST data base-4 of 2000 templates is 0.067 s. It is indeed a fast search process compared to the time consumption for matching an input with 2000 fingerprints in the data base.

B. Comparison of the Continuous Retrieval on NIST Data Base

The continuous classification approach proposed in [16], which is better than the approach [14], was also tested on the data set 2. Fig. 8 compares the results reported in [16] with those of this work, Consistent performance improvement of our approach is visible over all penetration rate in Fig. 8 where significant performance improvement is achieved in the area of higher retrieval efficiency. In addition, an important penetration rate of 5.22% is given in [16], which leads to no error in the incremental retrieval if a perfect matching algorithm is applied to prevent further retrieval just after the right candidate is

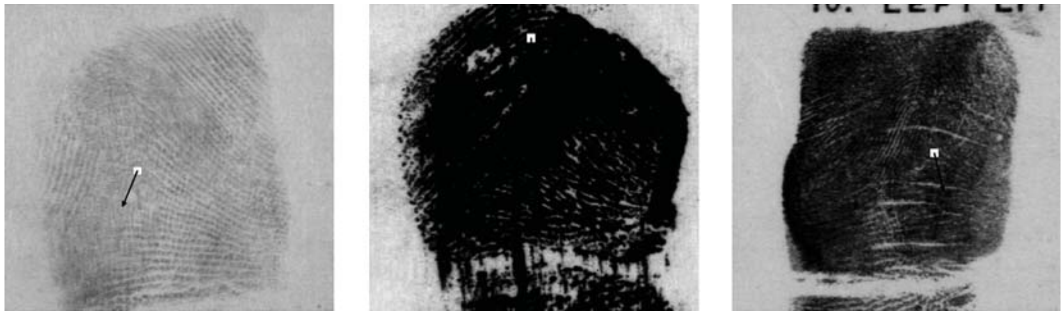

Fig. 7. Three fingerprint examples with wrongly located reference points represented by the small squares.

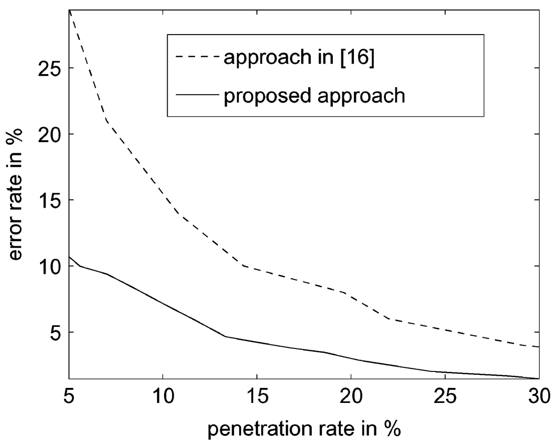

Fig. 8. Retrieval results of the proposed approach and the approach in [16].

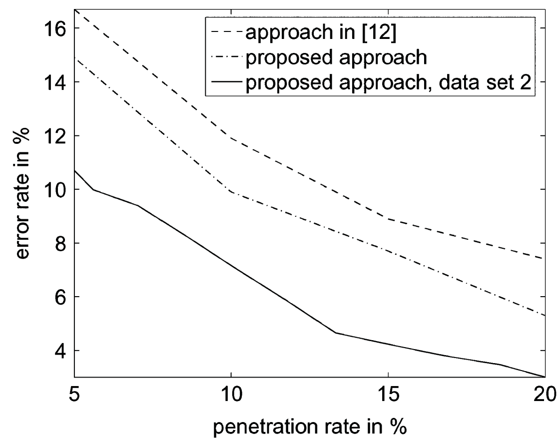

Fig. 9. Retrieval results in [12] and of the proposed approach on the same data base as in [12] and on data set 2.

retrieved for each input fingerprint. Our proposed approach achieves 2.93% for such an indicative penetration rate.

The fingerprint indexing approach based on minutia points was proposed in [11]. The retrieval performance was further improved in [12] by adding two new features. The better performed approach [12] was tested on the second 1000 fingerprint pairs of NIST data base-4. Fig. 9 shows the results reported in [12] and our approach on the same data set. Our approach outperforms the one proposed in [12] consistently for about 2% at all penetration rates. As this test data base is not of natural distribution, we also plot in Fig. 9 the retrieval results of our approach on the data set 2 that has natural distribution for further comparison.

C. Implication of the Retrieval Results

Let ε_1 and ξ_1 denote the false match and nonmatch rates of a fingerprint verification algorithm, respectively. ε_N and ξ_N represent the false match and nonmatch rates of an identification system on a data base of N fingerprints, respectively. Under some simplified assumptions, ε_N and ξ_N with and without a retrieval engine were computed using ε_1 and ξ_1, together with the retrieval error ζ and penetration rate p in [1], [30]. Applying only the verification algorithm, the false nonmatch rate has no change $\xi_N = \xi_1$ but the false match rate deteriorates from ε_1 to $\varepsilon_N = 1-(1-\varepsilon_1)^N$. If the data base is filtered by a retrieval algorithm, formulae of $\xi_N = \zeta+(1-\zeta)\xi_1$ and $\varepsilon_N = 1-(1-\varepsilon_1)^{pN}$ are given in [1], [30]. In the following examples, the same assumptions as in [1] and [30] are applied in calculating ε_N and ξ_N of an identification system.

If a verification algorithm with $\xi_1 = 5\%$ and $\varepsilon_1 = 0.005\%$ is directly applied to an identification system on the NIST data base-4 of 2000 fingerprints, ε_N will deteriorate to 9.52%. The application of the proposed retrieval algorithm with $p = 20\%$ and $\zeta = 2.87\%$ results in an increase of ξ_N from 5% to 7.73% and a decrease of ε_N from 9.52% to 1.98%. The proposed retrieval algorithm achieves zero error rate $\zeta = 0$ at the penetration rate of $p = 74.96\%$. At this operation point, the retrieval algorithm, which does not cause any increase of ξ_N, reduces ε_N from 9.52% to 7.22%.

If we retrieve fingerprints incrementally, we can achieve zero retrieval error $\zeta = 0$ by stopping the retrieval if and only if the input is matched with the retrieved template by a matching algorithm. The proposed retrieval algorithm achieves $p = 2.93\%$ if a perfect matching algorithm is applied. Thus, the penetration rate is 2.93% for the matched inputs and 100% at worst for the nonmatched inputs. The average penetration rate is at worst $p = 2.93\%(1-\xi_1) + 100\%\xi_1 = 7.78.\%$. Applying such an incremental retrieval, $\xi_N = 5\%$ remains unchanged and ε_N decreases from 9.52% to 0.78% compared to applying the verification algorithm only.

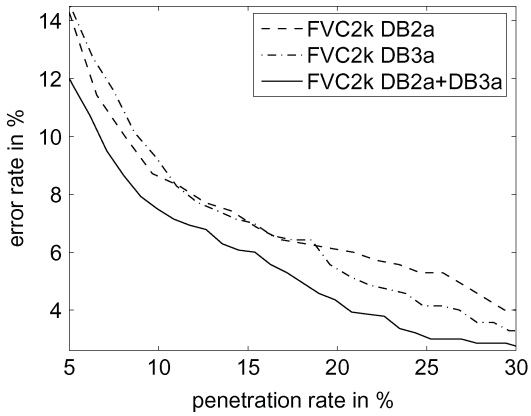

Fig. 10. Retrieval results on the FVC2k data bases and on the mixed data base.

D. Continuous Retrieval on FVC Data Base

This experiment tests the proposed approach on the online data bases. Two data bases (FVC2k Db2_a and Db3_a) [32] containing 1600 fingerprints (eight impressions per finger) are used in the experiment. Fig. 10 shows the retrieval error rates against the efficiency for these two data bases. Fingerprints of Db2_a have a higher image quality than those of Db3_a. At a lower penetration rate, successful retrieval needs closer similarity between the input and the template fingerprints, which is more sensitive to the image quality. Therefore, Db2_a has better retrieval performance than Db3_a at lower penetration rates. However, Db2_a has a worse retrieval performance than Db3_a at higher penetration rates. A partial fingerprint whose core point is near the image edge or out of the image is the culprit. Db2_a has more such partial fingerprints than Db3_a, which fails to be retrieved even at high penetration rates.

We further test the retrieval performance on the combined data base that contains all fingerprints of both Db2_a and Db3_a. Fig. 10 shows that the retrieval performance is better than those on the separate Db2_a and Db3_a. This is not a surprise because fingerprints of the same finger are captured by the same sensor but fingerprints of different fingers may originate from different types of sensors.

E. Results on Data-Base Clustering

It is not appropriate to compare the retrieval performance of a continuous classification-based approach with that of an exclusive classification-based method as there is an essential difference between them: the former requires to compare an input feature with features of all fingerprints in the data base and the latter does not. This may result in a significant retrieval time difference for a large data base. Although data-base clustering definitely reduces the retrieval accuracy and efficiency due to the quantization of the feature space and the number of retrieved fingerprints, it avoids the exhaustive comparisons, which greatly speeds up the retrieval process for a large data base. Therefore, the proposed clustering-based approach is comparable to the exclusive classification in terms of the time consumption for their retrieval application to the automated fingerprint identification system.

In addition to the experiments on the whole NIST data base-4, results on data set 2 are also given to show more indicative performance of the proposed method. The first fingerprint instances are partitioned into clusters, while the second instances serve as input fingerprints to be compared with the cluster prototypes. The number of clusters is initially set to be 70. After the K-means algorithm converges, we merge small clusters and split large ones and resume running it with the modified prototypes. This clustering algorithm finally produces 78 and 55 clusters for the NIST data base-4 and data set 2, respectively.

We compare the retrieval error at about the same retrieval efficiency. Most automated exclusive classification methods classify fingerprints into four or five classes. The penetration rate is 20% if a perfect classifier is applied to partition the NIST data base-4 into five classes that have the same occurrence frequency in the data base. It will increase to 28% if two classes (plain and tented arches) are merged into one. Some researchers weigh the classification results or construct a subset (data set 2) according to the natural fingerprint distribution for testing. For the weighted classification results or on the data set 2, the penetration rate is 29.48% and 29.69% for the five and four classes, respectively. Therefore, in our experiments, the proposed clustering-based approach retrieves fingerprints at the penetration rates of 20%, 28%, 29.48%, and 29.69%, respectively. We compare our results with those of the exclusive classification methods presented in the literature.

Table I shows the error rates on the NIST data base-4 ("whole") or its second half ("2nd h.") of 12 published exclusive classification methods and the proposed clustering-based retrieval approach. All error rates in the same column are at the same penetration rate p. The number of classes classified by the exclusive classification methods and whether weighting is used in the error calculation are denoted as "5 c.," "4 w. c.," etc. in the first row of the table. Note that, as some ambiguous fingerprints in the data base are assigned to two class labels by human expertise, the error rates of approaches [4], [2], [5], [3], [33], [34], [7], and [35] are calculated by assuming a correct classification if any one of the two class hypotheses is the output of the classifier. This assumption gives a lower error rate than that obtained by using only one class label. In addition, some error rates of approaches [3], [9], [7] are obtained at a 1.8% rejection rate.

It is worth mentioning that the classification error of the exclusive classification is not fully equivalent to the retrieval error for identification. For a fingerprint identification system, fingerprint retrieval is successful only if the input fingerprint and the corresponding one in the data base are consistently classified in the same class. Nevertheless, experimental results in Table I demonstrate that the proposed approach achieves better performance than various exclusive classification methods for the retrieval application to a fingerprint identification system. It also shows the advantages of the proposed machine-generated flexible fingerprint classes against the human-predefined exclusive classes.

VI. Conclusion

This work proposed a fingerprint retrieval framework using the orientation field as the main feature and the dominant ridge distance as an auxiliary feature. These coarse level features are not closely correlated with minutiae that are often used for the

TABLE I
ERROR RATES OF VARIOUS EXCLUSIVE CLASSIFICATION METHODS AND THE PROPOSED CLUSTERING-BASED APPROACH ON NIST DATA BASE-4

method year and source	p=20 5 c.	p=29.5 5 w. c.	p=28 4 c.	p=29.7 4 w. c.	test set
Candela et al. 95 [4]	–	–	11.4	6.1	2^{nd} h.
Karu & Jain 96 [2]	14.6	11.9	8.6	9.4	whole
Hong & Jain 99 [34]	12.5	10.6	7.7	–	whole
Jain et al. 99 [3]	10	7.0	5.2	–	2^{nd} h.
Jain & Minut 02 [33]	–	–	8.8	9.3	whole
Cappelli et al. 99 [16]	–	12.9	–	–	set 2
Cappelli et al. 99 [5]	7.9	6.5	5.5	–	2^{nd} h.
Senior 01 [8]	–	–	–	5.1	2^{nd} h.
Yao et al. 01 [7]	10.7	9.0	6.9	–	2^{nd} h.
Marcialis et al. 01 [9]	12.1	9.6	–	–	2^{nd} h.
Zhang & Yan 04 [35]	15.7	–	7.3	–	whole
Park & Park 05 [6]	9.3	–	6.0	–	whole
proposed	5.3	3.3	3.5	3.2	whole
proposed	4.7	2.9	3.2	2.8	set 2

fine matching in automated fingerprint verification and identification systems. Consequently, the proposed retrieval approach not only speeds up the identification process but also alleviates the accuracy deterioration of the fingerprint identification.

The introduced auxiliary feature, the dominant ridge distance, is more robust to noise than the simple average ridge distance of a fingerprint. The proposed distance measure, which evaluates the inconsistency of orientation differences and the proposed regional weighting scheme, visibly improves fingerprint retrieval performance. In addition, the suggested retrieval threshold slightly improves the retrieval performance. Experiments on the NIST data base-4 demonstrate that the proposed framework outperforms the previous continuous classification and minutia-based indexing approaches in terms of fingerprint retrieval accuracy.

This work further proposed a retrieval scheme that facilitates the fingerprint retrieval without the one-by-one exhaustive comparisons of an input with all fingerprints in the data base. The data base is partitioned into clusters and an input fingerprint only needs to be compared with the cluster prototypes. Since fingerprints always exist near the cluster boundaries regardless of how well the clusters are formed, it is crucial to retrieve, instead of one, often a few clusters to solve this problem. Although the clustering-based approach results in a drop in accuracy or efficiency due to the quantization of the feature space, it facilitates fast fingerprint retrieval. In terms of the retrieval speed, this method is comparable to the exclusive classification for the application of the automated fingerprint identification. Experiments show that the proposed clustering-based approach achieves better retrieval results than various exclusive classification methods.

A problem of the proposed framework is its dependency on the accuracy and robustness of the reference point detection. In fact, a substantial portion of the retrieval errors is caused by the falsely or inconsistently detected reference point due to poor fingerprint quality. For a fingerprint retrieval system that requires higher accuracy, a fingerprint rejection engine can be applied to exclude such fingerprints at a price of lower retrieval efficiency.

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Xudong Jiang (SM'06) received the B.Eng. and M.Eng. degrees in electrical and electronic engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 1983 and 1986, respectively, and the Ph.D. degree n electrical and electronic engineering from the University of German Federal Armed Forces, Hamburg, Germany, in 1997.

From 1986 to 1993, he was a Lecturer with UESTC and from 1993 to 1997, he was a Scientific Assistant with the University of German Federal Armed Forces. From 1998 to 2002, he was a Senior Research Fellow with Nanyang Technological University (NTU), Singapore, where he developed a fingerprint verification algorithm that achieved the most efficient and second most accurate fingerprint verification in the International Fingerprint Verification Competition. From 2002 to 2004, he was a Lead Scientist and Head of the Biometrics Laboratory at the Institute for Infocomm Research, Singapore. Currently, he is a Faculty Member and serves as the Director of the Centre for Information Security, the School of Electrical and Electronic Engineering, NTU, Singapore. His research interests include pattern recognition, signal and image processing, computer vision, and biometrics.

Dr. Jiang received two science and technology awards from the Ministry for Electronic Industry of China.

Manhua Liu received the B.Eng. degree in automatic control from North China Institute of Technology, Taiyuan, China, in 1997 and the M.Eng. degree in automatic control from Shanghai JiaoTong University, Shanghai, China, in 2002. She is currently pursuing the Ph.D. degree at Nanyang Technological University (NTU), Singapore

Her research interests include biometrics, pattern recognition, image processing, and machine learning.

Alex C. Kot (F'06) received the B.S.E.E. and M.B.A. degrees from the University of Rochester, Rochester, NY, and the Ph.D. degree from the University of Rhode Island, Kingston.

Currently, he is with Nanyang Technological University, Singapore, where he headed the Division of Information Engineering at the School of Electrical and Electronic Engineering for eight years and is currently a Professor and Vice Dean (Research) for the School of Electrical and Electronic Engineering. He has published extensively in the areas of signal processing for communication, biometrics, data hiding, and authentication.

Dr. Kot served as Associate Editor for IEEE TRANSACTIONS ON SIGNAL PROCESSING, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—PART II and IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY. He was Guest Editor for IEEE and EURASIP journals. Currently, he is Associate Editor for IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—PART I and *EURASIP JASP*. He has served on many conference committees and technical committees, including co-chairing the IEEE International Conference on Image Processing (ICIP) in 2004. He was an IEEE Distinguished Lecturer from 2005–2006.