Latent Fingerprint Indexing: Robust Representation and Adaptive Candidate List

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***Abstract*— Efficiently identifying the mated gallery fingerprint of a latent fingerprint in a large database requires a highly accurate and efficient fingerprint matching algorithm. The common strategy to achieve this goal is to combine an efficient indexing algorithm with a slow but accurate matching algorithm. Despite of the importance of latent indexing, it has received far less attention than rolled and plain fingerprint indexing. Due to the small fingerprint area, poor image quality and huge variety in information quantity of latent fingerprints, existing rolled and plain fingerprint indexing approaches cannot be simply migrated to the latent fingerprint indexing. In this paper, we propose (1) a multi-scale fixed-length representation approach for latent fingerprint indexing, and (2) a fingerprint information quantity estimation approach for adaptive candidate list reduction. The representation scheme is designed to deal with small finger area and low image quality of latents. The information quantity of a latent is a predictor of the indexing score of its mated gallery fingerprint and thus can be used to determine a proper threshold for its candidate list. Extensive experimental results on NIST SD27, MOLF, N2N, and Hisign latent fingerprint databases show that the proposed method achieved the state-of-the-art indexing accuracy on latent fingerprints, and significantly improved the efficiency of state-of-the-art latent matching algorithm.**

***Index Terms*— Latent fingerprint indexing, fixed-length representation, information quantity prediction, candidate list reduction.**

I. Introduction

LATENT fingerprints collected from crime scenes are widely used to identify suspects by law enforcement agencies worldwide [1]. Latent fingerprint recognition usually works in identification mode, namely, it involves searching against large database of rolled/plain fingerprints, which puts forward high demand for accuracy and efficiency of fingerprint matching. A common solution of large-scaled automated fingerprint identification systems is to apply a fingerprint indexing algorithm first to select a short candidate list for elaborate matching by a complicated fingerprint matcher. Such a scheme is able to improve the matching speed while maintaining the identification accuracy. Recently, a lot of research has focused on latent fingerprint feature extraction [2]–[10] and matching [11]–[15], but little attention has been paid to latent fingerprint indexing.

Most existing fingerprint indexing approaches are developed for rolled or plain fingerprints [16]. A fingerprint indexing method mainly contains three steps: (1) extract features to construct the fingerprint representation, (2) calculate the indexing scores between query and gallery fingerprints, and (3) produce a candidate list by applying a reduction criterion to the indexing scores. The first two steps are very related to each other and have been the focus of most fingerprint indexing studies, while the third step has received much less attention [17].

Fingerprint representation and similarity calculation have great influence on the time and space complexity and the accuracy of an indexing approach. In existing indexing approaches, a fingerprint is represented by a variable-length or fixed-length feature vector. Minutiae based representations [18]–[22] widely used in fingerprint indexing are usually variable-length. These approaches extract local minutiae descriptors as the variable-length representations of fingerprints. Since the minutiae set is unordered and variable-length, indexing algorithms often need to construct complex data structures such as hash table in the off-line stage in order to improve the searching speed in the on-line stage. When the size of database is very large, such approaches may encounter the problems of large storage consumption and slow searching speed. Besides, such approaches rely heavily on reliable minutiae extraction, which is a challenging problem for latents. Fixed-length representation based approaches use traditional fingerprint features (such as orientation field, period map, singular points) [23]–[26] or features extracted by deep learning [27]–[31] to construct fingerprint representations. Compared with variable-length representations, the storage space of fixed-length ones is usually smaller and the searching speed is faster. However, existing fixed-length representations are designed for rolled and plain fingerprints, without considering the small finger area and low quality of latent fingerprints.

In existing fingerprint indexing approaches, fixed threshold and fixed rank are the two most commonly used criteria of reducing candidate list. The fixed threshold criterion selects the gallery fingerprints whose indexing scores are greater than or equal to a given threshold, while the fixed rank criterion selects those whose ranks are higher than or equal to a given rank.

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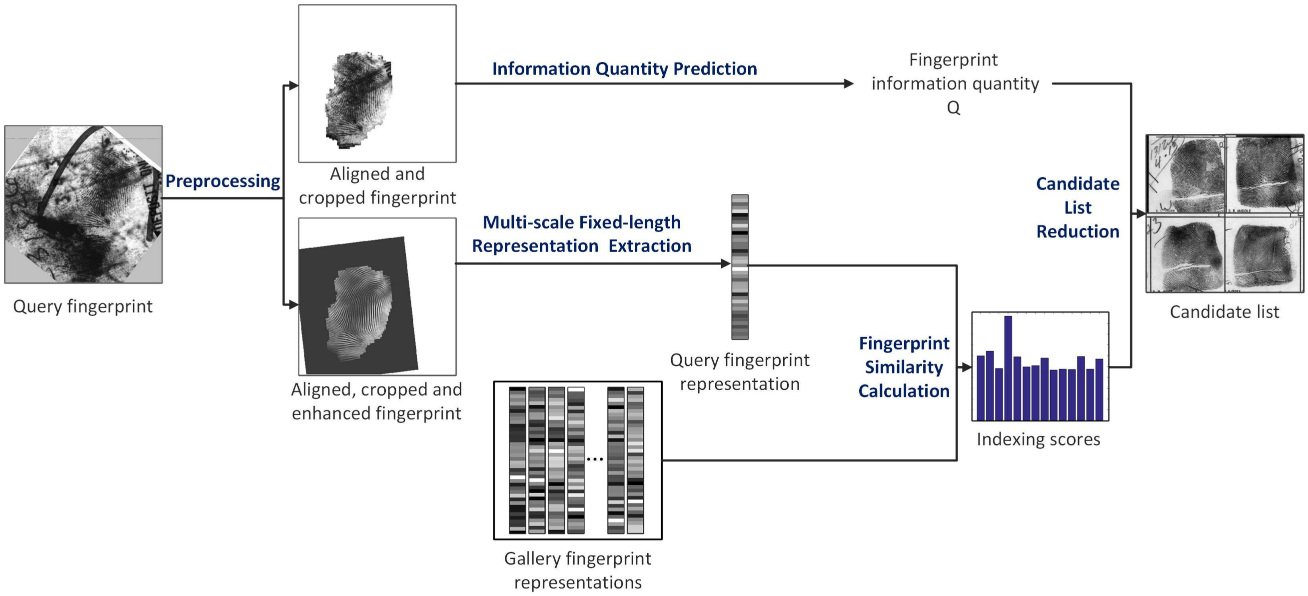


Fig. 1. The flowchart of the proposed fingerprint indexing algorithm. Query fingerprint is firstly aligned with the estimated pose and enhanced for better recognition. Then the representation of the whole fingerprint image is extracted through the proposed multi-scale fixed-length representation algorithm. Indexing scores are obtained by computing the similarity between query and each gallery fingerprint. At the same time, the query fingerprint information quantity is predicted by the proposed information quantity prediction network. The final candidate list is selected based on the information quantity of query fingerprint and indexing scores.

Compared with these two simple criteria, the two reduction criteria using variable threshold proposed in [17] were shown to be able to reduce the candidate list significantly in a closed-set scenario and improve the indexing performance. These two criteria in fact try to predict the rank of mated gallery fingerprint based on the distribution of quantity indexing scores sorted in descending order. If the top indexing scores drop rapidly, the mate is predicted to be at high rank, and thus a short list is selected. If the top indexing scores are similar, the mate is predicted to be at low rank, and thus a long list is retained. However, when the query fingerprint does not have mated fingerprint in the gallery database, which is common in an open-set scenario, top indexing scores are very low and quite similar. In such cases, candidate list cannot be reduced effectively by these two criteria. Besides, the information quantity of latent fingerprints varies greatly, which makes it more difficult to determine the appropriate length of candidate list in latent fingerprint indexing.

In order to overcome the above limitations in major steps of fingerprint indexing algorithms when applied to latents, we propose a multi-scale fixed-length representation, which can effectively deal with incomplete and low-quality fingerprints, and propose a fingerprint information quantity estimation method to predict the indexing score of mated gallery fingerprint, which can be used to determine candidate list adaptively. The flowchart of the proposed indexing algorithm is shown in Fig. 1.

Fingerprints are represented with features extracted from image patches at different scales and locations to consider the incomplete fingerprint area. Multi-scale patches capture different level fingerprint features, and all patches can cover the whole fingerprint. The similarity between two fingerprints is computed by the weighted sum of local patch similarities, where weights are learnt to indicate the importance of different patches. Only image patches in valid and overlapping fingerprint area are used to measure fingerprint similarity; thus image patches with strong background noise are excluded. In this way, the score fusion helps consider the valid area of fingerprints. The similarity calculation of two fingerprints is fast and simple since fingerprints are aligned.

The proposed candidate list reduction criterion relies on the information quantity (IQ) of latent fingerprints, which is linked to the indexing score of its mated gallery fingerprint. A fingerprint with high information quantity indicates a high genuine score, while a fingerprint with low information quantity indicates a low genuine score. Based on the predicted information quantity, the candidate list is reduced adaptively while ensuring that mated gallery fingerprints are kept in the candidate list with high probability.

Extensive experiments were conducted on four latent databases, Hisign latent fingerprint database, NIST SD27 [32], MOLF [33], and N2N [34] latent databases to evaluate the performance of four fingerprint indexing approaches. Experimental results showed that the proposed multi-scale fixed-length representation approach outperformed two variable-length approaches [20], [22] and a state-of-the-art fixed-length approach [30]. Identification experiment was also performed to examine the added value of the proposed indexing approach. By using the proposed indexing approach to choose candidate list for a state-of-the-art latent fingerprint matching approach [15], we can improve the identification efficiency by 5 times while slightly improving the accuracy, or improve the efficiency by 20 times with negligible impact on the accuracy. Indexing experiments were also conducted on two rolled fingerprint databases, NIST SD4 [35] and NIST SD14 [36], and the proposed approach was compared with existing fixed-length representation approaches. The experimental results showed that our approach generalized well to rolled fingerprints, with performance comparable to the state-of-the-art.

II. Related Work

A. Fixed-Length Representation of Fingerprints

The fixed-length representation can be classified into two classes: alignment-based and alignment-free approaches.

Alignment-based approaches [23], [24], [27]–[30] firstly align the input fingerprints with respect to estimated fingerprint pose or certain reference frame, then extract features from the whole fingerprint images as the fixed-length representation. Traditional methods [23]–[26] apply level-1 features such as orientation fields and period maps. Recently, with the great progress of deep learning, deep features greatly improve the indexing performance. They usually train a classification task or a metric learning task, and take the output of the last fully connected layer or the last convolutional layer in the CNN model as the fixed-length representation. The deep features extracted from the whole aligned fingerprint images [28]–[30] contain mainly texture based information. To improve the indexing performance, minutiae information [29], [30] is further introduced to capture local features simultaneously. However, features extracted from whole fingerprint images will inevitably be affected by incomplete fingerprints. Song and Feng [27] propose an indexing approach, referred to as PDC in [30], which fuses the deep features from different regions of the image pyramid and concatenates them into a fixed-length vector, but still does not consider very incomplete fingerprints.

An example of alignment-free approach is the which is a minutiae based fixed-length representation proposed by Song *et al.* [31], referred to as MDC in [30], which aggregates local minutiae descriptors to obtain a global fingerprint representation. They train an AggregationNet containing one dimensional convolution and pooling to fuse all the minutiae descriptions into a single feature representation. This approach does not require fingerprint alignment, but its performance depends heavily on the minutiae detection accuracy.

Representation and similarity measure in the proposed approach are inspired by PDC [27], which extracts deep features from local patches at different scales and locations, and computes the similarity of two fingerprints by the weighted sum of local similarities. But different from PDC, the weights in the proposed approach are learned to improve the indexing performance, and only the local patches in the overlapping area contribute to the similarity fusion. Experimental results showed that our scheme is more suitable for latents.

B. Reduction Criterion of Candidate List

Given a large number of gallery fingerprints and a query fingerprint whose mated fingerprint may or may not be contained in the gallery, a candidate list reduction criterion is employed to reduce the candidate list. Suppose that the mated fingerprint is in the gallery, the ideal reduction criterion is to select the mated fingerprint and only those non-mated ones whose similarities are not smaller than the mated one. On the contrary, suppose that there is no mated fingerprint in the gallery, the ideal reduction criterion is to output an empty list.

The fixed threshold [37], [38] and fixed rank [19], [39] are the most popular reduction criteria in the literatures. The fixed threshold criterion selects candidates with indexing score higher than a given threshold while the fixed rank criterion return a fixed length candidate list after sorting. These two criteria use the same criterion for all query fingerprints, which may lead to long candidate list when the threshold setting is loose or the rank is low, and may lose true matches when the threshold setting is tight or the rank is high.

Cappelli *et al.* [17] proposed two criteria based on analyzing indexing scores, one variable threshold on score difference and the other variable threshold on score ratio. In these two criteria, the list is truncated before the first score such that the difference or the ratio between it and a reference score is larger than a given threshold, where the reference score is determined by a predefined parameter. Their criteria select the candidate list based on the sorted indexing scores. When the top scores decrease rapidly, a shorter candidate list is obtained; otherwise, a longer list is obtained. But when there are no mated fingerprints of the query fingerprint in the database, which is very common in an open-set scenario, the top scores tend to be very low and similar, and these two criteria will instead select a long candidate list.

In this work, we propose an information quantity based reduction criterion where the number of candidates is selected based on the estimated fingerprint information quantity. The fingerprint information quantity is predicted through an end-to-end deep neural network from the query fingerprint. The proposed prediction method joint trains the feature extraction and prediction model, which is quite different from the methods using handcrafted features and shallow models [40]–[44]. Besides, the proposed prediction method quantifies the indexing performance as the information quantity of false matching rate, which is a direct predictor of a matcher's performance. On the other hand, the proposed reduction criterion predicts the rank of mated fingerprint (related to FMR) based on deep learning, while the two criteria in [17] is based on rule. Our method does not need to analyze the indexing scores, but is based on the query fingerprint itself, so it can handle both open-set and close-set scenario.

III. Proposed Algorithm

In this section, we describe the proposed latent fingerprint indexing algorithm, including the fingerprint preprocessing, multi-scale fixed-length representation, fingerprint information quantity prediction, information quantity based candidate list reduction criterion, and implementation details of these modules.

A. Fingerprint Preprocessing

To achieve satisfactory performance on latent fingerprints, the input fingerprints should be preprocessed firstly.

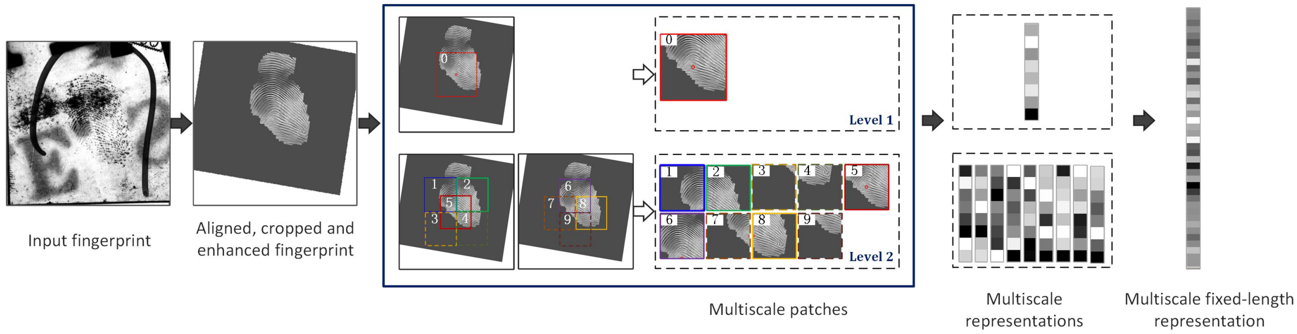


Fig. 2. The flowchart of extracting a multi-scale fixed-length representation of a fingerprint. Given an input fingerprint, it is aligned, cropped and enhanced firstly. Then multi-scale patches are cropped and patch descriptors are extracted. Valid patches (area is over a given threshold) are marked with solid lines while others are marked with dashed lines. Only valid patches are considered in computing similarity.

When extracting the fingerprint representation, th input fingerprint is required to be enhanced, cropped by the estimated fingerprint ROI, and aligned with estimated fingerprint pose. When predicting the information quantity of latent fingerprint, only alignment and cropping is required. Original fingerprint is better for information quantity prediction.

We use FingerNet [10], which shows great performance on latent fingerprints, to obtain the enhanced fingerprints and the fingerprint ROI. Then, to align the latent fingerprints in advance accurately, the pose estimation method proposed by Gu *et al.* [45] is used since the voting based center estimation is suitable for partial fingerprints. Here the fingerprint pose is composed of the fingerprint center, which is defined as the upper core of the fingerprint, and the fingerprint direction, which is vertical to the finger joint. After the center and direction is estimated, the fingerprint is aligned to make the center located at the origin of the coordinate system and the direction along the y-axis direction.

B. Multi-Scale Fixed-Length Representation

The flowchart of the proposed fixed-length representation of fingerprints is shown in Fig. 2. After preprocessing the input fingerprint, multiple fingerprint patches at different scales and locations are cropped from the aligned fingerprint image, and the deep features are extracted from each fingerprint patch. The similarity of fingerprint patches at the same scale and location is estimated by the cosine distance of descriptors, and the similarity of a pair of fingerprints is estimated by the weighted sum of all the similarities of local paired patches whose overlapping foreground area is over a given threshold. In this way, only the overlapping area of a pair of fingerprints are considered in the score calculation, which can be better applied to latent fingerprints with small and irregular valid area. As shown in Fig. 3, when the overlapping area of a pair of mated fingerprints in the fingerprint center is small, the similarity score estimated by only the central image patch is low. But when fusing the similarities of local patches in the overlapping area, the local image patches can cover the overlapping area completely and no more background noise is introduced.

In the following, we introduce three components, patch extraction, patch descriptor extraction and weight learning.

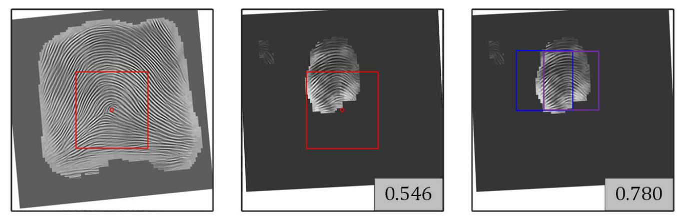


Fig. 3. The effective of the similarity fusion on incomplete fingerprints. The similarity between a pair of mated fingerprint is low when the overlapped area in the single image patch centered on the fingerprint center is small. When using multi-scale patches to represent the fingerprints, the completeness of at least one local patch can be guaranteed under different incomplete conditions, and thus the genuine indexing score calculated by fusing the local patches is higher.

1) Multi-Scale Patches: Since the fingerprint center is defined as the upper core of fingerprints, the area around the center contains the most important identification information of fingerprints. Therefore, the fingerprint patches are cropped around the the fingerprint center.

A two scale pyramid of fingerprint patches is built. The first level contains N_1 patches centered on the fingerprint center, which aims at capturing the whole features of fingerprints. The patch size is $P_r \times P_r$ for rolled fingerprints and $P_p \times P_p$ for plain and latent fingerprints. The second level contains N_2 smaller patches, whose size is $P_s \times P_s$. This level of patches helps extract local features only from effective areas so as to represent the fingerprint more robustly. Finally, totally $N_p = N_1 + N_2$ patches are extracted from each fingerprint image.

2) Fingerprint Patch Description: We apply the deep neural network to extract features of local patches since CNN based features have achieved outstanding performance on multiple fingerprint recognition tasks [46]–[48]. We train N_p different networks for the N_p patches at different scales and positions. The procedure of training these networks are the same, and only the training data is different.

The ResNet-18 architecture is adopted for training the networks. To ensure the same input image size of $P_s \times P_s$, the training image patches are resized with bilinear interpolation no matter what size it is. For each CNN network, we take it as a multi-classification problem, and use the addition angular margin loss [48] which shows great performance on face recognition.

3) Weight Learning: After obtaining the deep features of local fingerprint patches, the weights of different patches are learnt. Considering a pair of fingerprints $\mathbf{X}$ and $\mathbf{Y}$ with N_p different patches $\mathbf{X} = \{x_1, x_2, \ldots, x_{N_p}\}$ and $\mathbf{Y} = \{y_1, y_2, \ldots, y_{N_p}\}$, respectively, their similarity is calculated by the weighted cosine distance between the features of corresponding patches. The weights α of local patches are learnt considering that different patches may have different discriminating ability. Only patches with fingerprint area S more than a given threshold τ are used. Therefore, the similarity of a pair of fingerprints is defined as

$$sim(\mathbf{X}, \mathbf{Y}) = 1 - \frac{\sum_{i=1}^{N_p} \alpha_i [S_{x_i} > \tau][S_{y_i} > \tau]\langle f_{x_i}, f_{y_i}\rangle}{\sum_{i=1}^{N_p} \alpha_i [S_{x_i} > \tau][S_{y_i} > \tau]}, \quad (1)$$

where $[\cdot]$ is the Iverson bracket, and $\langle f_{x_i}, f_{y_i}\rangle$ is the inner product of the fixed-length vectors f_{x_i} and f_{y_i} extracted by the network.

To learn the weight of each patch, we use the following loss functions, similar with that in [49].

$$D = \text{argmin} \sum_{i=1}^{N_p} \alpha_i (\langle f_{x_i}, f_{y_i}\rangle - \langle f_{x_i}, f_{z_i}\rangle + \beta)$$
$$\text{s.t} \quad \sum_{i=1}^{N_p} \alpha_i = 1, \alpha_i \geq 0, \quad (2)$$

where f_{x_i} and f_{y_i} are the feature vectors extracted from fingerprints $\mathbf{X}$ and $\mathbf{Y}$ of the same identity, and f_{z_i} is the feature vector extracted from a fingerprint $\mathbf{Z}$ from a different identity. β is the margin. We use the the algorithm of Lagrange multipliers to find the minimum of loss function D, and the weight α. By minimizing the loss, the distance between the same identity is expected to be close and the distance between different identities to be far.

4) Training Data: To train the multi-scale fixed-length representation network, multiple impressions of one fingerprint are necessary. We obtain such fingerprints by simulating the distortion, difference appearance, and valid area of fingerprints. For a rolled fingerprint, we first use the learned distortion field model [50] to synthesize the distortion. The first two dimensional principal component coefficients are randomly selected in a range of $[-1, 1]$ to generate a distortion field, which is applied to the input fingerprint to obtain a distorted one. Then the difference appearance of fingerprints is simulated by histogram matching, which transforms an image into a specific gray distribution. The gray histograms of fingerprints in FVC2004 DB1A database are selected randomly as the target. After that, the different valid area of fingerprints is simulated by cropping the fingerprint image with the ROI of any rolled fingerprint from another identity. We use the first 24,000 pairs of fingerprints in NIST SD14 to simulate another 4 different impressions for each fingerprint. Note that it is a convention to use the first 24,000 pairs of fingerprints in NIST SD14 as training set. Finally, we obtain 24,000 classes of fingerprints, 10 impressions in each class for training.

To learn the weights of different local patches, the Hisign Rolled fingerprint database is used. We select the first $N_w = 3,000$ fingerprints, two images for each fingerprint. Using the multi-scale fixed-length representation method, the similarity between the first image of each rolled fingerprint and the second image of all other rolled fingerprints can be calculated. The similarity of N_w pairs of fingerprints as genuine matches, and the similarity of N_w pairs of unmatched fingerprints with the highest score as impostor matches are used for the weight training. In this way, hard negative samples helps improve the fingerprint recognition performance.

C. Fingerprint Information Quantity Prediction

We propose an end-to-end deep neural network for information quantity prediction from the preprocessing latent fingerprint, and the predicted information quantity is further adopted in the reduction criterion of candidate lists.

In the following, we will introduce the information quantity determination, the features used for information quantity prediction, and the model architecture used in the prediction network.

1) Information Quantity Determination: The fingerprint information quantity is defined as a predictor of the proposed multi-scale fixed-length representation based fingerprint matching performance. The performance is required to be quantified firstly. Given the similarity of a pair of fingerprints, the likelihood that they come from a genuine match or impostor match can be obtained in conjunction with the distributions of genuine scores and impostor scores. We use the False Match Rate (FMR) corresponding to the genuine score to directly measure the likelihood. Suppose that the gallery fingerprints are of high quality, and the matching performance between a pair of mated latent and gallery fingerprints is only affected by the latent fingerprint quality. If a latent fingerprint is of high quality, the likelihood of the latent and its mated gallery fingerprint being predicted from the same individual is high based on their score, and the uncertainty is low. Similarly, if a latent fingerprint is of low quality, the latent and its mated gallery fingerprint is predicted to be a genuine match with high uncertainty. Therefore, we define the information quantity of a fingerprint based on the uncertainty of the false match rate.

Concretely, suppose the score distribution of all impostor matches is $p(s|I)$, and the score of a pair of genuine match fingerprints is t. The FMR corresponding to this genuine match is computed as

$$\text{FMR(t)} = \int_t^1 p(s|I)ds = 1 - \int_0^t p(s|I)ds = 1 - F(t), \quad (3)$$

where $F(t)$ is the Cumulative Distribution Function (CDF) of the impostor distribution. We use

$$Q = -\log_2(\text{FMR}) \quad (4)$$

as the information quantity of the latent fingerprint in the genuine match. Fig. 4 shows the distribution of impostor matches, the FMR curve and two examples with different latent fingerprint information quantity. The larger score corresponds to lower FMR, and thus indicates higher fingerprint information quantity, and vice versa.

We use latent fingerprint database as training data, which contains pairs of rolled and latent fingerprints. Each fingerprint

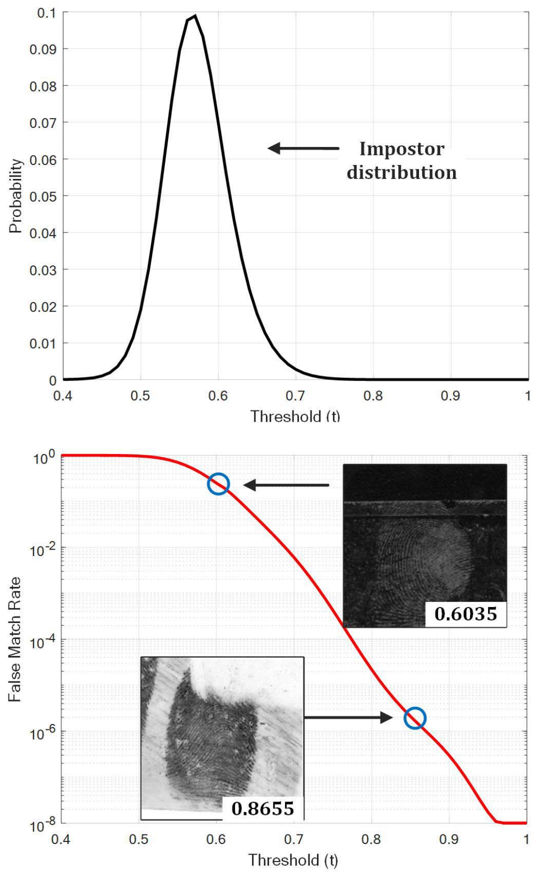


Fig. 4. The distribution of impostor scores and the FMR curve. Scores have been normalized to [0, 1]. Two examples with different latent fingerprint information quantity are marked on the curve, where higher indexing score corresponds to a lower FMR, and thus indicates a higher fingerprint information quantity, and vice versa.

is first enhanced by FingerNet and sent into the network to extract the multi-scale fixed-length representations. Then we calculate the similarity of each latent fingerprint and all rolled fingerprints to obtain the scores of genuine matches and impostor matches. All the scores are normalized to [0, 1].

2) Features: Given an input latent fingerprint, its ROI is firstly estimated by FingerNet [10], and it is masked out the background region to reduce the effect of the background noise with the estimated ROI. Then it is aligned by the estimated pose, similar with the procedure in the multi-scale fixed-length representations. After that, the deep neural network is applied to predict the information quantity. By aligning and masking out the fingerprint image, the deep neural network is expected to capture the valid area of fingerprint and the finger position, which are commonly used features used in previous work [41], [42] and are related to the fingerprint information quantity.

In addition to considering the valid area of fingerprint and the finger position features, the ridge clarity is incorporated with deep features extracted from whole fingerprint images for better prediction. In this way, we take benefits of both deep features and traditional handcrafted features.

We add extra supervision map to make the deep features pay more attention to the clarity of ridges. The design of the

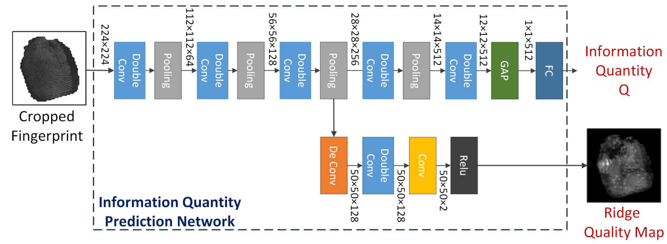


Fig. 5. The architecture of the fingerprint information quantity prediction network.

supervision map takes the idea in [51], [52], which measures the local ridge quality by the consistency of orientation flow.

For an input fingerprint, the FingerNet estimates the probability distribution of orientation field, that is the probabilities of n discrete angles at each pixel. We then use the kurtosis and skewness of estimated probability distribution of orientation field to measure the discernibility of the fingerprint ridges. At each pixel, a $N_{ori} = 90$ dimensional vector $P = \{p_1, p_2, \ldots, p_{N_{ori}}\}$ is predicted, and the kurtosis and skewness are defined as:

$$\mathrm{Kurt}(P) = \frac{\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^3}{\sigma^3} \tag{5}$$

$$\mathrm{Ske}(P) = \frac{\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^4}{\sigma^4} \tag{6}$$

where $\bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i$ is the mean, and $\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(p_i - \bar{p})^2}$ is the standard deviation. In this way, a kurtosis K and a skewness map S can be obtained from an orientation distribution map. The supervision map is finally defined as their dot product.

3) Model: An end-to-end network is used to predict the fingerprint information quantity, as illustrated in Fig. 5. We take it as a regression problem, where the input is a maskout fingerprint image, and the output is a single numerical value to predict the fingerprint information quantity.

a) Model architecture: We use the VGG-13 architecture as the basic network and crop it before the pool5 layer. There are five double-conv blocks, and the first four blocks are followed by a max pooling layer. In general, the fingerprint information quantity can be assessed by the quality and quantity of features. The quality usually refers to the discernibility and reliability of the fingerprint ridges, and the quantity refers to sufficiently large and clear friction ridge areas. We design the network according to these two points.

From the quality perspective, extra supervision is added at pool3 in order to make the extracted features pay more attention to the clarity of ridge lines. The supervision layers contains a deconv layer, a double-conv layer, a conv layer and a Relu layer.

From the quantity perspective, after the feature extraction module, a global average pooling layer is followed to get the average local patch quality. Since the background of input fingerprint image is set to 255 with the estimated ROI, the global average pooling layer is able to get the information of fingerprint ridge area. Finally, a fully connected layer is used to predict the information quantity of the input fingerprint image.

b) Loss function: The loss function here contains two parts, the MSE loss L_Q which minimizes the error of the predicted information quantity and the ground truth one, and the MSE loss L_{map} which evaluates the estimation accuracy of ridge clarity map. The total loss is the weighted sum of these two losses:

$$L = L_Q + \lambda L_{map}, \tag{7}$$

where λ is the weight coefficient.

4) Training Data: Hisign latent fingerprint database is used here as the training data of the prediction network, which contains more than 10,000 pairs of rolled and latent fingerprints. Since the number of impostor matches is near 1×10^8, the fingerprint information quantity of all latent fingerprints varies in the range of $[0, 30]$.

Due to the lack of public latent fingerprint databases, the Hisign latent fingerprint database is used both for training and testing. When testing the proposed indexing algorithms, cross-validation experiment is conducted to ensure that the training and test data do not coincide. Concretely, the databases are split into 5 parts where 4 parts for training and 1 part for test. We train 5 different models with different training data, test on the remaining data, and finally obtain the information quantity prediction on the whole databases.

D. Information Quantity Based Candidate List Reduction

By predicting the information quantity, the indexing performance of the query fingerprint is predicted. After that, we propose two reduction criteria based on the predicted information quantity, the variable threshold and the variable rank based criterion.

1) IQ Based Variable Threshold Criterion: After predicting the information quantity of the query fingerprint Q_{pre} by the proposed prediction network, the FMR corresponding to the score between the latent fingerprint and its mated gallery fingerprint is predicted as $\text{FMR}_{pre} = 2^{-Q_{pre}}$, according to the definition of information quantity.

Since the FMR corresponding to the genuine score of the latent fingerprint, the genuine score can be estimated from the predicted information quantity. Given the predicted FMR, the possible score of the latent fingerprint and its mated gallery fingerprint is estimated as $s_{pre} = F^{-1}(1 - \text{FMR}_{pre})$, where F^{-1} is the inverse function of the CDF of impostor distribution. Then the indexing score against all gallery fingerprints is calculated according to Eq. 7, and the maximum indexing score is considered as s_{max}. Only the candidates whose scores are higher than a filtering threshold are selected, where the threshold $s_{filter} = \min(s_{pre}, s_{max})$.

2) IQ Based Variable Rank Criterion: As the FMR corresponds to a latent fingerprint is the percentage of impostor pairs whose matching scores are greater than or equal to the genuine score, the FMR also corresponds to the rank of the genuine score among all false matching scores.

If suppose that the score distribution of all false matches in a latent fingerprint database is the same as that of the false matches of a specific latent fingerprint, then the rank of the mated gallery fingerprint is $r_{pre} = \text{FMR}_{pre} \times N_{gallery} = 2^{-Q_{pre}} \times N_{gallery}$, where $N_{gallery}$ is the gallery size. However, due to the diversity of the latent fingerprint information quantity, the above hypothesis is not tenable, therefore, we add an additional correction coefficient to modify the predicted rank. The modified rank can be estimated as $r_{pre} = \text{FMR}_{pre}^{-\frac{1}{b}} \times N_{gallery} = 2^{-\frac{Q_{pre}}{b}} \times N_{gallery}$. The parameter b is set as 2 in experiments according to the relationship between FMR and rank in latent databases. After that, we sort the indexing scores and select the candidates whose ranks are higher or equal to the predicted rank.

Based on the proposed two criteria, in the closed-set scenario, a shorter candidate list is selected for fingerprints with high information quantity and a longer candidate list is selected for fingerprints with low information quantity. In the open-set scenario, when the fingerprint is with high information quantity, the predicted indexing score is high and the predicted rank is low, and thus fewer fingerprints are selected, which is different from other criteria.

E. Implementation Details

When extracting the multi-scale fixed-length representations, the first level contains $N_1 = 1$ patch while the second level contains $N_2 = 9$ patches. The patch size in the first level is $P_r = 448$ for rolled fingerprints and $P_p = 287$ for plain fingerprints. The patch size in the second level is $P_s = 224$. The threshold τ to judge whether the foreground area of an image patch is large enough is set as 0.6 in Hisign latent fingerprint database and 0.4 in other databases.

The networks including the VGG and ResNet in the two proposed modules are trained with PyTorch from scratch on NVIDIA GTX 1080 Ti GPUs. When training the feature extraction network, the learning rate is 0.1 and decays at 0.95 rate every 10 epochs. The batch size is 32, and models are trained for over 30 epochs. When training the fingerprint information quantity prediction network, the learning rate is set as 0.01. Weight decays 0.95 every 5 epochs. The coefficient of λ in Eq. 7 is 0.1. The margin β in Eq. 2 is 0.1.

The deep models (VGG and ResNet) used as tools in the proposed fingerprint indexing framework can be replaced by other models, such as DenseNet, etc. FingerNet can also be replaced by other fingerprint enhancement techniques. We did not optimize deep models and enhancement algorithms since it is beyond the scope of this study.

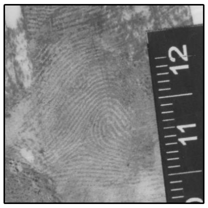
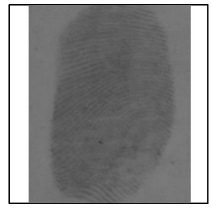
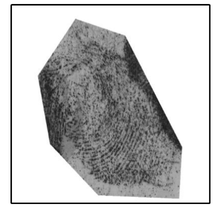
IV. Experiments

In this section, we carry out several experiments to evaluate the proposed fingerprint indexing algorithm. In the following, we will first introduce all the databases used in the experiments, then the indexing performance evaluation on latent and rolled fingerprints, respectively, the performance of combining latent fingerprint indexing with fingerprint matching, the effect of the information quantity based reduction criterion, and the efficiency.

A. Databases

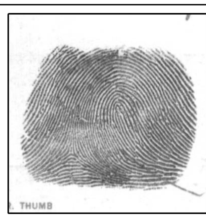
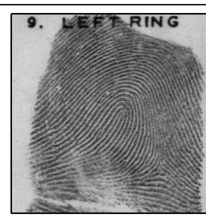
We use seven different kinds of databases in the experiments including four latent and three rolled fingerprint databases.

TABLE I
LATENT FINGERPRINT DATABASES USED IN THE EXPERIMENTS

Databases	Hisign latent Fingerprint Database[1]	NIST SD27 [32]	MOLF [33]	N2N [34]
Image				
Collection Environment	crime scenes	crime scenes	laboratory	laboratory
Description	10,458 pairs of latent and mated rolled fingerprints	258 pairs of latent and mated rolled fingerprints	1,000 pairs of latent and mated slap fingerprints[3]	3,392 latent fingerprints[3] and 2,000 mated rolled fingerprints
Experiments	Training the information quantity prediction network and testing[2]	Testing	Testing	Testing

[1] Rolled fingerprints in Hisign latent Fingerprint Database are different from those in Hisign Rolled Fingerprint Database.
[2] Cross validation is used to ensure that there is no overlap in the training and testing data.
[3] Not all the fingerprints in the MOLF and N2N databases are used. The details of fingerprint selection are provided in Section IV.A.

TABLE II
ROLLED FINGERPRINT DATABASES USED IN THE EXPERIMENTS

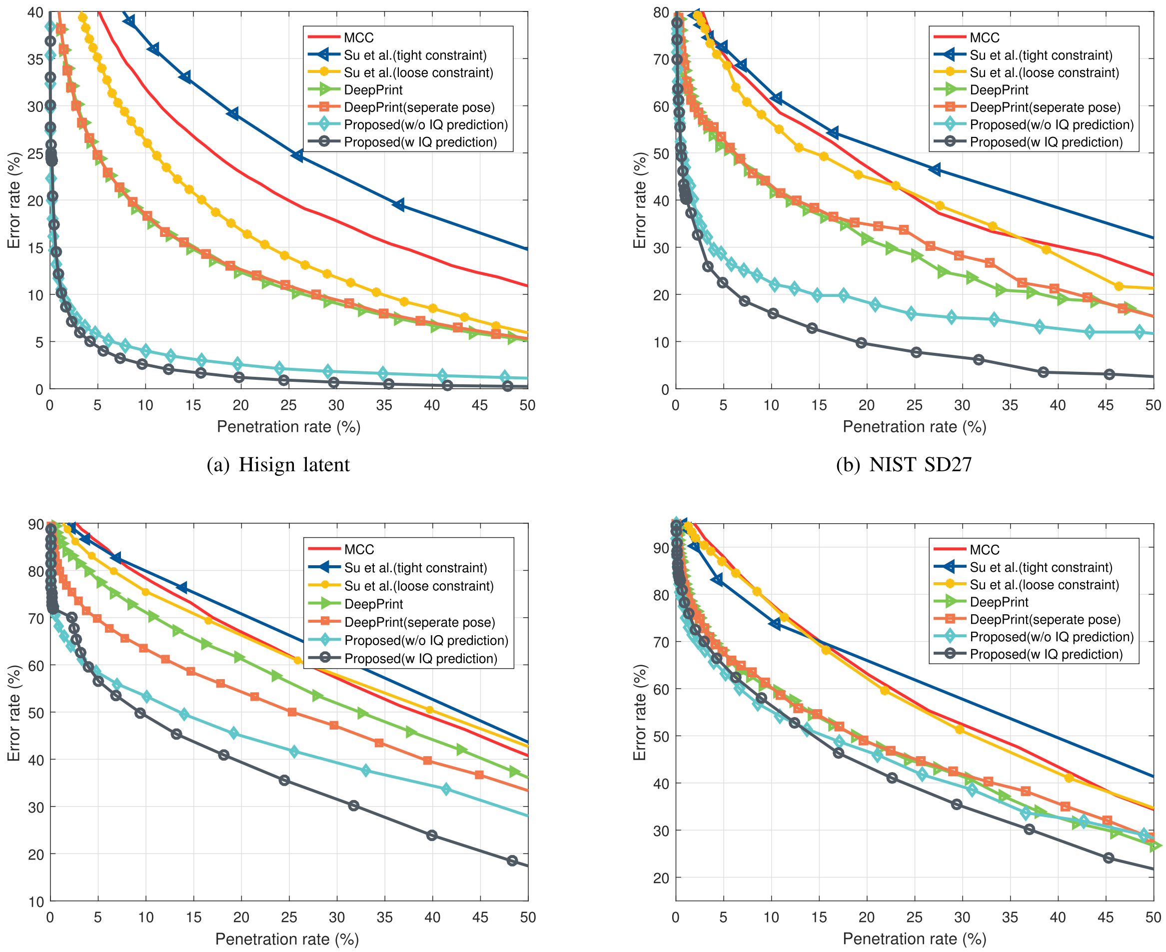
Databases	NIST SD14 [36]	NIST SD4 [35]	Hisign Rolled Fingerprint Database
Image			
Description	27,000 pairs of mated rolled fingerprints	2,000 pairs of mated rolled fingerprints	139,329 rolled fingerprints from 39,500 fingers, average 3 impressions for each finger
Experiments	Training local patch descriptors and testing[1]	Testing	Learning the weights of local patches[2] and testing as the gallery database

[1] The first 24,000 pairs are used for training the patch descriptors and the last 2,700 pairs are used for testing.
[2] The first 2 impressions from the first 3,000 fingerprints are used to learn the weights of local patches, and the first impression of all the fingerprints are used as extra gallery fingerprints.

Table I and Table II introduce all the fingerprint databases and their usages in the experiments and gives one fingerprint example in each dataset. Because not all the latent fingerprints in the MOLF and N2N databases are used in the experiments, the details of fingerprint selection is introduced in the following, and the filename lists of fingerprints selected are submitted as a supplementary material.

The MOLF database has five subsets. We choose the DB3_A plain subset and the DB4 latent subset, and the first impression of each finger for the indexing experiments, and thus obtain 1,000 pairs of latent and plain fingerprints. Because the fingerprint quality in this database is poor, the fingerprints which cannot be segmented and enhanced by FingerNet are excluded. Therefore, 790 pairs of latent and plain fingerprints are used in our experiments.

The N2N database is released by NIST, which has rolled, plain, and latent fingerprints. We select the baseline U subset in the SD302b set as the reference datasets, which has 2000 rolled fingerprints from 200 subjects, and the SD302e subset as the query datasets, which has 10,000 latent fingerprints from the same 200 subjects. Since the correspondences between the rolled fingerprints and latent fingerprints are unknown, and only subject level correspondences are known, the following method is applied to obtain the corresponding rolled fingerprint of each latent fingerprint. The fingerprints are firstly enhanced by FingerNet for better recognition. Then for each latent fingerprint, its indexing scores with 10 rolled fingerprints from the same subjects are computed by VeriFinger 11.2 [53]. The rolled fingerprint with the maximum score is set as the corresponding one, and the correspondences



(a) Hisign latent (b) NIST SD27

(c) N2N (d) MOLF

Fig. 6. Indexing performance on four latent databases. The proposed indexing approach without the fingerprint information quantity prediction and other approaches use the fixed threshold criterion, and the proposed with the IQ prediction uses the proposed IQ based variable threshold criterion.

have been checked manually. Finally, by excluding low quality fingerprints that the fingerprint area cannot be extracted by FingerNet or the minutiae extracted are too few for VeriFinger to output matching scores, we obtain the corresponding rolled fingerprints of 3,392 latent fingerprints and conduct the indexing experiments on these fingerprints.

B. Indexing Performance on Latent Fingerprints

Indexing experiments are conducted on four latent fingerprints for evaluation. The latent fingerprints in each database is searched against all rolled fingerprints in the same database.

To our best knowledge, none of recent fixed-length fingerprint representation works have conducted experiments on latent fingerprints, and their code has not been released. We reimplemented the DeepPrint [30] and trained it using our training images, and compare the proposed approach with it. The parameters used are the same with that in their paper, but the localization estimation and fingerprint representation modules are trained separately. The localization estimation module is trained firstly, using the ground-truth alignment parameters as supervision. Then the network parameters in the localization estimation module are fixed and the fingerprint representation module is trained.

TABLE III

EXPERIMENT SETTINGS OF APPROACHES TO BE COMPARED

Experiments	Approaches	Settings
Latent Indexing	DeepPrint [30]	Our reimplementation
	Su *et al.* [22]	Original code
	Cappelli *et al.* [20]	Public SDK
Rolled Indexing	DeepPrint [30]	Reported performance[1]
	MDC [31]	Reported performance[1]
	FingerPatches [29]	Reported performance[1]
	PDC [27]	Reported performance[1]
Latent Matching	LatentAFIS [15]	Original public code

[1] The performance is cited from DeepPrint paper [30].

The proposed method is also compared with the variable-length representations proposed by Su *et al.* [22] and Cappelli *et al.* [20]. The settings of all the approaches to be compared are listed in Table III. For fair comparison, all the latent fingerprints have been enhanced with FingerNet, and the same pose estimation approach [45] is adopted for the proposed and the method of Su *et al.* [22]. The DeepPrint incorporates the pose estimation and representation extraction

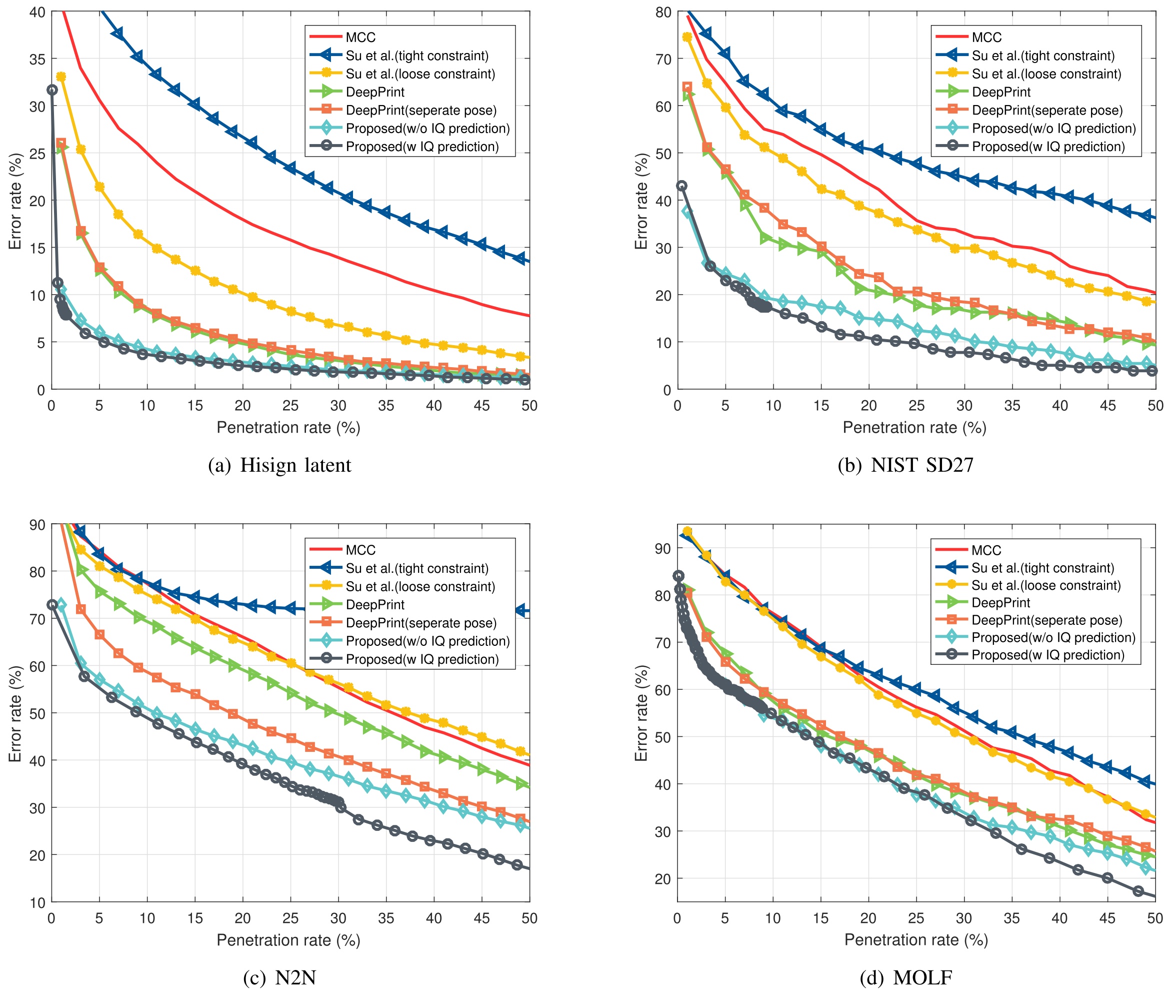


Fig. 7. Indexing performance on four latent databases. The proposed indexing approach without the fingerprint information quantity prediction and other approaches use the fixed rank criterion, and the proposed with the IQ prediction uses the proposed IQ based variable rank criterion.

in an end-to-end network, therefore, we report two results with two different pose estimation approaches. The minutiae used in the variable-length representations are extracted also by FingerNet. In the approach of Su *et al.*, the parameter of location uncertainty and direction uncertainty is set to control the effect of pose. We set $e_l = 200, e_\theta = 40$ as the loose constraint, and $e_l = 60, e_\theta = 10$ as the tight constraint, similar with that in [54].

Two versions of our approach are tested, one using only the proposed representation (labeled by Proposed (w/o IQ prediction) in Fig. 6 and Fig. 7) and the other using both the proposed representation and the IQ based candidate list reduction criterion (labeled by Proposed (w IQ prediction) in Fig. 6 and Fig. 7). When evaluating the proposed representation, the same candidate list reduction criteria is used for all approaches for fair comparison. The ratio of average length of the candidate list to the number of gallery fingerprints is seen as the penetration rate, and the percentage of query fingerprints whose mated fingerprint is not in the candidate list is taken as the error rate. By changing the rank or the threshold, we can draw the trade-off curve between the error rate and the penetration rate.

The indexing performances on four latent databases to evaluate the proposed IQ based variable threshold criterion are shown in Fig. 6, and the indexing performances to evaluate the proposed IQ based variable rank criterion are shown in Fig. 7. From these figures, we observe that

- The two minutiae based approaches achieves comparable indexing performance on four latent databases. The performance of Su's method with loose constraint is obliviously superior to Su's with tight constraint on all databases. This indicates that the estimated pose on latent fingerprints are still not precise, so that more constraint is required in indexing. Loose constraint induces more comparisons, and thus much more time is required.
- DeepPrint performs better than two minutiae based approaches but worse than ours, and the performances of DeepPrint with different pose estimation approaches are comparable on three databases. Therefore, the performance of DeepPrint on latent fingerprints is worse, probably because the global feature representation may introduce too more background noise, and so as to influence the performance.

TABLE IV
INDEXING PERFORMANCE ON ROLLED FINGERPRINT DATABASES NIST SD4 AND NIST SD14

Reduction Criteria	Fingerprint Representation	NIST SD4		NIST SD14	
		ER@PR=1.0%	Rank-1 Accuracy	ER@PR=1.0%	Rank-1 Accuracy
Fixed rank	PDC [27]	6.7%	-	-	-
	MDC [31]	0.8%	-	0.4%	-
	Finger Patches [29]	**0.17%**	**99.27%**	0.11%	99.04%
	DeepPrint [30]	0.25%	98.70%	0.07%	99.22%
	Proposed representation	0.30%	98.80%	**0.04%**	**99.81%**
Proposed variable rank criterion	Proposed representation	0.25%	98.80%	0.04%	**99.81%**
Proposed variable threshold criterion	Proposed representation	**0.05%**	98.80%	**0.00%** [1]	**99.81%**

[1] The error rate drops to 0 when penetration rate is 0 64%

- The proposed multi-scale fixed-length representation method achieves the best performance on four databases, which shows the superiority of the proposed approach on latent fingerprint indexing. The proposed information quantity based criteria further improves the indexing performance.
- It should be noted that the performances of the proposed approach on four latent fingerprint databases are quite different. This may be because the latent fingerprints in Hisign latent fingerprint database and NIST SD27 were collected from crime scenes, while the latent fingerprints from the other two databases MOLF and N2N were simulated in the laboratory setting. The characteristic of simulated fingerprints is quite different from those collected in real crime scenes. Besides, since we train the deep models (fingerprint representation model and IQ prediction model) using the fingerprints in the Hisign latent fingerprint database, the performances on MOLF and N2N databases are not optimal.

C. Indexing Performance on Rolled Fingerprints

For rolled fingerprint databases NIST SD4 and NIST SD14, we use the pose estimation method proposed by Yin *et al.* [55], which shows great performance on rolled fingerprints and is quite efficient, and do not conduct the fingerprint enhancement and cropping. The same evaluation criterion as previous studies is used for fair comparison. In the whole 2000 fingerprints in NIST SD4 database and the last 2700 pairs of fingerprints in NIST SD14 database, the "F" impressions are used as gallery sets, and the "S" impressions are used as query.

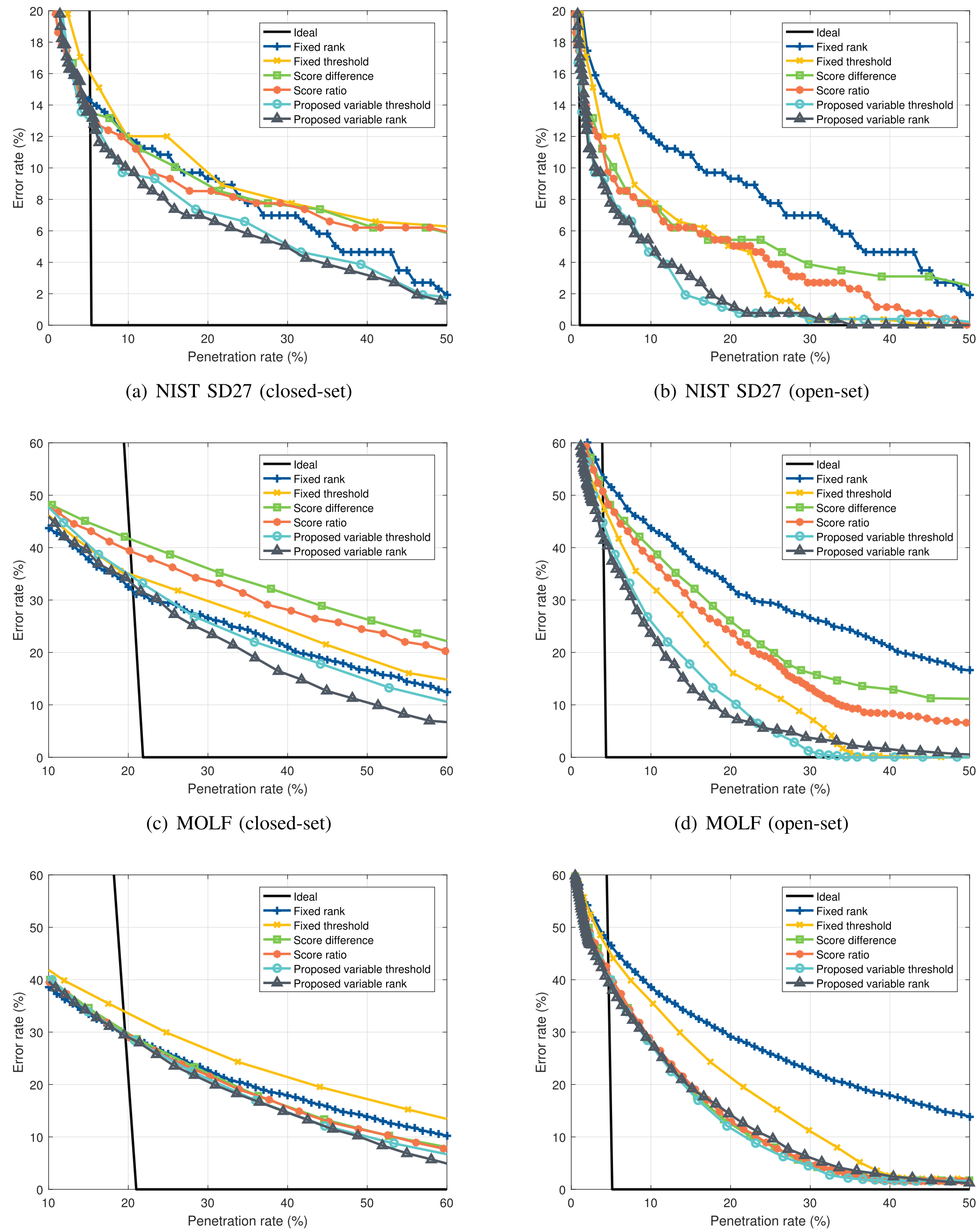
All the approaches to be compared use the fixed rank reduction criterion to select the candidate list, and thus the proposed approach take both the fixed rank reduction criterion and the proposed IQ based criterion. We report the error rate at 1% penetration rate and the rank-1 accuracy on NIST SD4 and NIST SD14 databases in the Table IV. The performances of approaches to be compared [27], [29]–[31] are all cited from DeepPrint [30]. On NIST SD4, the Finger Patches [29] outperforms all other methods, and our performance is better than DeepPrint. On NIST SD14, the performance of our method is the best. After applying the proposed information quantity based criteria, the error rate can be greatly reduced at the same penetration rate. Due the the small size of gallery databases and the high quality of rolled fingerprints, the performance of recent deep learning based indexing algorithms on these two datasets is saturated, and the gap between them is relatively small.

D. Combining Latent Fingerprint Indexing With Fingerprint Matching

Fingerprint indexing is a key strategy to reduce the search space and false matches in large database retrieval. To evaluate the comprehensive performance of fingerprint indexing and matching algorithms, we combine the proposed fingerprint indexing approach and the state-of-the-art fingerprint matching approach LatentAFIS [15] against a larger number of gallery fingerprints. Concretely, the proposed approach is firstly used to select the candidate list for each latent fingerprint. Then, the open-source LatentAFIS recomputes the scores between the query fingerprint and gallery fingerprints in candidate list, and produces the identification result or constructs a shorter candidate list with the fixed threshold criterion for the final manual determination.

We conduct the experiments on four latent fingerprint database, and the gallery consists of 39,500 rolled fingerprints in the Hisign Rolled fingerprint database and all the mated rolled or plain fingerprints in each database. Here only 532 latent fingerprints in the N2N database are used, because only on these fingerprints the LatentAFIS can segment the fingerprint ROI and extract features, and their similarities with all gallery fingerprints can be calculated. The filename lists of these fingerprints selected are also submitted as a supplementary material.

The combination performance is shown in Table V. Due to the variable length of candidate list, average length is used. Before combination, fingerprint matching between the query fingerprint and all the gallery fingerprints are required, which is rather time consuming. When combining the proposed indexing approach with the fingerprint matching, a large number of fingerprints are excluded in advance. After excluding 80% fingerprints, not only the total search time of searching a latent against a gallery of 39,500 fingerprints is reduced by 5 times, but also the rank-1 accuracy improves on three



(a) NIST SD27 (closed-set) (b) NIST SD27 (open-set)

(c) MOLF (closed-set) (d) MOLF (open-set)

(e) N2N (closed-set) (f) N2N (open-set)

Fig. 8. Comparison of seven candidate list reduction criteria applied to the proposed indexing approach on NIST SD27, MOLF and N2N databases.

databases. The improvement is probably due to the exclusion of false matches.

E. Candidate List Reduction Criterion

The proposed two fingerprint information quantity based reduction criteria are evaluated and compared with the other criteria defined in [17] in both closed-set and open-set scenario. Indexing scores are computed by the proposed multi-scale fixed-length representation.

The experiments are conducted on NIST SD27, MOLF and N2N latent databases, which are different types of fingerprint databases. The experiments in the closed-set scenario and open-set scenario are carried out as follows, taking the NIST SD27 database as an example:

- The rolled fingerprints in the Hisign Rolled fingerprint database and the rolled fingerprints in the NIST SD27 database are used as gallery.
- In the closed-set scenario, the latent fingerprints in the NIST SD27 database are used as query fingerprints.
- In the open-set scenario, the latent fingerprints in the NIST SD27 database and the latent fingerprints in the Hisign latent fingerprint database are used as query fingerprints. The number of the latent fingerprints in the Hisign latent fingerprint database is four times as large

TABLE V
THE RANK-1 SEARCH ACCURACY OF COMBINING THE PROPOSED APPROACH WITH LATENTAFIS

Methods	PR	Hisign Latent	NIST SD27	MOLF	N2N
LatentAFIS [15]	100%	95.07%	68.60%	**27.34%**	59.96%
Proposed variable	40%	95.14%	67.83%	26.96%	60.90%
rank criterion	20%	**95.28%**	68.60%	26.08%	59.96%
+ LatentAFIS	10%	95.14%	68.22%	24.94%	58.08%
Proposed variable	40%	95.22%	**69.38%**	27.09%	**61.65%**
threshold criterion	20%	95.23%	**69.38%**	26.08%	61.09%
+ LatentAFIS	10%	95.00%	68.60%	25.57%	60.71%

as that of latent fingerprints in the NIST SD27 database, that is, only 20% of query fingerprints have mated fingerprints in the gallery. The proportion is based on the actual statistics of local police department. Specially, the query fingerprints which have mated gallery fingerprints is 24.49% in N2N database, since the number of latent fingerprints in N2N database is 3392, and that in Hisign latent fingerprint database is 10458.

In the closed-set scenario, the trade off between penetration rate and error rate is used as the evaluation criterion. In the open-set scenario, the same trade off curve is used as evaluation criterion, but the error rate is computed only from the latents with mated gallery fingerprints.

The performance of seven candidate list reduction criteria is shown in Fig. 8. Given one query fingerprint, the ideal criterion selects those candidates whose scores are larger than the filtered threshold which is defined by the scores of genuine matches. At this time, the error rate is zero, and the penetration rate is taken as the ideal penetration rate. Once the threshold increases, all the mated gallery fingerprints are excludes, and thus the error rate is one. Therefore, the performance after the ideal penetration rate is more important. In the closed-set scenario, the two score based criteria proposed in [17] achieve comparable performance with fixed rank and fixed threshold criteria on NIST SD27 and N2N databases, and inferior to them on MOLF database, probably because the score based criteria select a longer candidate list when the similarities are similar. The proposed information quantity based criteria perform better on all three fingerprint databases. In the open-set scenario, the proposed two information quantity based criteria improve the performance more significantly, since it excluded a large number of candidates with low indexing scores, which with high confidence are non-mated fingerprints.

F. Distribution of Latent Fingerprint Information Quantity

We show the distribution of ground-truth fingerprint information quantities on four latent fingerprint databases in Fig. 9. The ground-truth fingerprint information quantities are computed from the genuine indexing score in each database and the impostor scores in Hisign latent fingerprint database. It can be seen from the figure that the information quantities of latent fingerprints collected from the crime scene is higher and diverse. The fingerprint information quantities in the Hisign latent fingerprint dataset is the highest, and that in the NIST SD27 dataset is medium. The information quantities of latent fingerprints collected from the laboratory is very low, which may be due to the poor quality and smaller valid area of the latent fingerprints in these two datasets. The huge difference in the information quantities of the two kinds of latent fingerprint databases also explains the different performance of the proposed approach on the two kinds of databases. Although the simulated latent fingerprints are quite different from the real ones, we also report the experimental performance on them, mainly in order to be consistent with the previous latent fingerprint identification papers. We did not optimize the performance on simulated fingerprints because they are less important than real latent fingerprints.

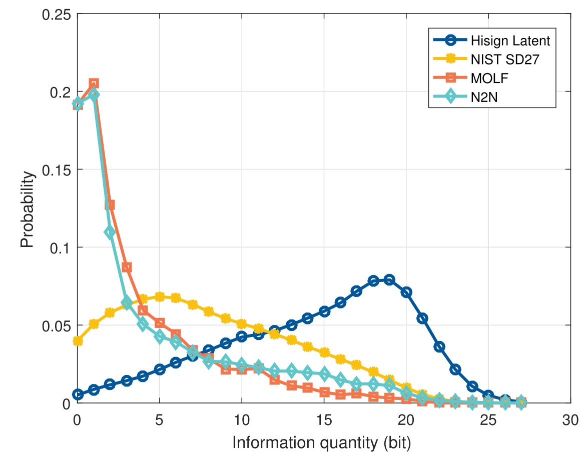


Fig. 9. Distribution of ground-truth fingerprint information quantities on four latent fingerprint databases.

Several examples in four latent fingerprint databases with different information quantities are shown in Fig. 10, which are sorted according to the ground-truth fingerprint information quantities. The fingerprints with unclear ridges, partial and small valid area have lower information quantities. The proposed information quantity prediction approach can predict accurately the information quantities of fingerprints with different valid area and ridge clarity.

G. Computational Efficiency

We compare the computational efficiency of the proposed indexing approach with the latent fingerprint matching approach LatentAFIS, and three indexing approaches, including two fixed-length representation approaches, the PDC and DeepPrint, and one variable-length representation approach [22].

The search times of the PDC, DeepPrint, and Su *et al.* are cited from their paper. The search time for DeepPrint is 51 milliseconds against 1.1 million background with an Intel Core i9-7900X CPU at 3.30 GHz, and that for PDC is 0.52 milliseconds against 2000 fingerprints with Intel Core i5 CPU at 2.6 GHz. Su *et al.* spends 24.43 milliseconds with loose constraint and 13.79 milliseconds with tight constraint when indexing one image from last 2700 pairs of fingerprints in NIST SD14 with C++ on a 2.5 GHz Intel Xeon CPU.

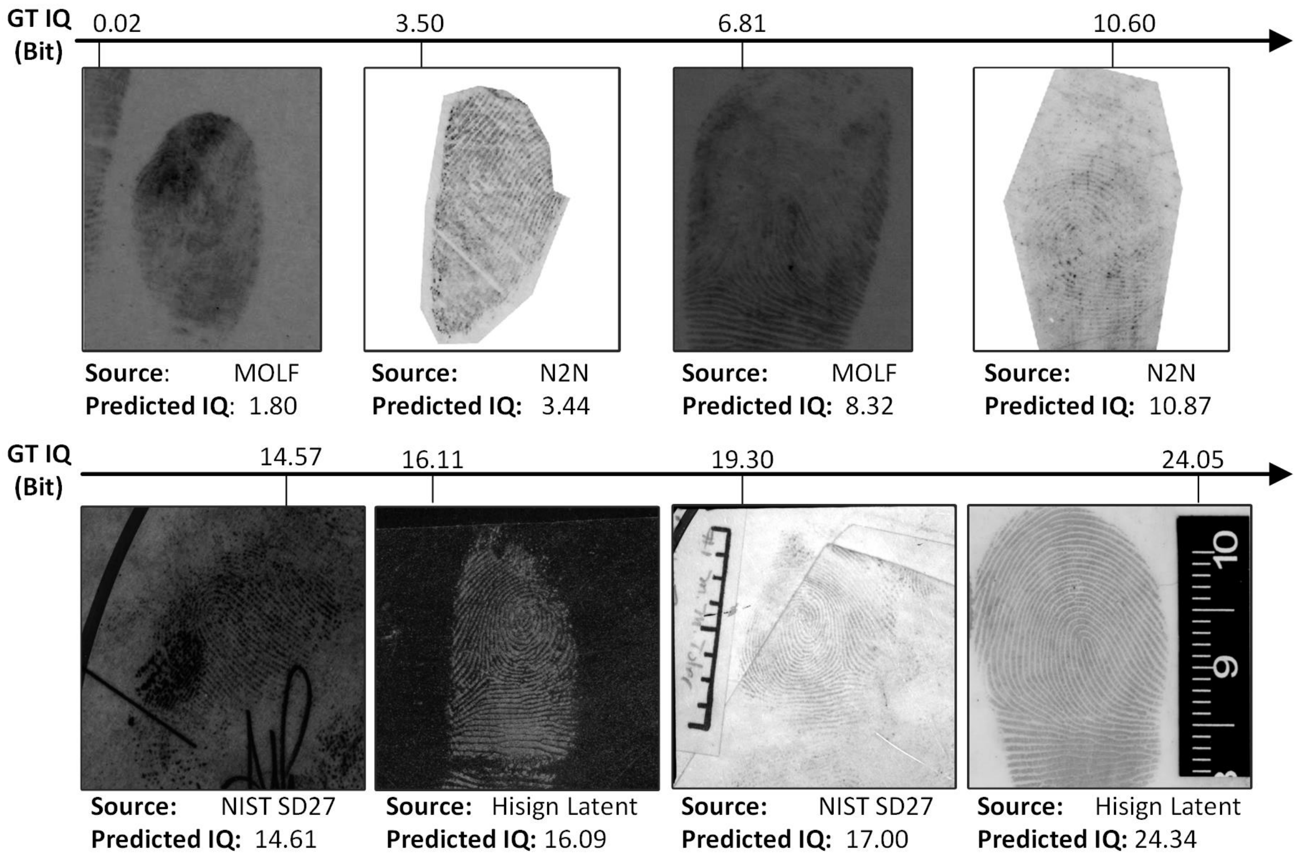


Fig. 10. Examples of fingerprints in four latent fingerprint databases of different information quantity.

TABLE VI
COMPUTATIONAL EFFICIENCY OF FINGERPRINT INDEXING AND MATCHING APPROACHES (SECONDS)

	Module	LatentAFIS [15]		The proposed	
		Latent	Rolled	Latent	Rolled
Feature extraction	Image enhancement	32.91	1.17	0.21	-
	Pose estimation	-	-	5.13	5.36
	Descriptor extraction	137.48	19.39	0.29	0.29
	IQ prediction	-	-	0.034	-
Matching		1.00×10^{-3}		3.02×10^{-7}	

Here are the search time for one query fingerprint against one gallery fingerprint, 4.64×10^{-8} seconds for DeepPrint, 2.60×10^{-7} seconds for PDC, and 5.11×10^{-6} seconds for the method of Su *et al.* with tight constraint and 9.05×10^{-6} seconds with loose constraint.

For fingerprint matching approach LatentAFIS and the proposed fingerprint indexing approach, we detail the time of each module on NIST SD27 database in Table VI. The pose estimation module is implemented in MATLAB on a PC with 2.50 GHz, and all other modules are implemented on a 2.10 GHz Intel Xeon CPU and NVIDIA GTX 1080 Ti. We can observe that the proposed approach is as efficient as PDC, but 7 times slower than DeepPrint, because the proposed approach and PDC require calculating the similarities of multiple local patches. The proposed approach is nearly 3000 times more efficient than LatentAFIS.

V. CONCLUSION

This paper aims to put forward solutions to the difficulties encountered in the very challenging latent fingerprint indexing problem, which has received little attention of researchers. To achieve this goal, we propose a latent fingerprint indexing algorithm, which consists of two key components, multi-scale fixed-length fingerprint representation, and fingerprint information quantity based candidate list reduction criterion. The proposed fingerprint representation pays more attention to the incomplete valid area of latent fingerprints. After obtaining the indexing scores, the fingerprints whose scores are higher than an adaptively determined threshold are included in the candidate list, where the threshold is related to the estimated latent fingerprint information quantity.

The proposed latent fingerprint indexing algorithm was tested on four latent databases and two rolled databases. Experimental results showed its better performance on latent fingerprints and ability to deal with rolled fingerprints. The proposed fingerprint information quantity based reduction criterion outperforms existing reduction criteria especially in open-set scenario. The work can be extended by (1) incorporating minutiae information to improve the discrimination of feature representation and the accuracy of information quantity prediction, and (2) conducting the indexing experiments on larger background databases.

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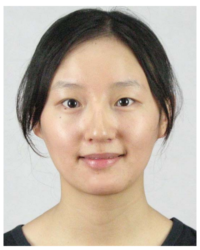

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