Narrow Fingerprint Template Synthesis by Clustering Minutiae Descriptors

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SUMMARY

Narrow swipe sensor has been widely used in embedded systems such as smart-phones. However, the size of captured image is much smaller than that obtained by the traditional area sensor. Therefore, the limited template coverage is the performance bottleneck of such kind of systems. Aiming to increase the geometry coverage of templates, a novel fingerprint template feature synthesis scheme is proposed in the present study. This method could synthesis multiple input fingerprints into a wider template by clustering the minutiae descriptors. The proposed method consists of two modules. Firstly, a user behavior-based Registration Pattern Inspection (RPI) algorithm is proposed to select the qualified candidates. Secondly, an iterative clustering algorithm Modified Fuzzy C-Means (MFCM) is proposed to process the large amount of minutiae descriptors and then generate the final template. Experiments conducted over swipe fingerprint database validate that this innovative method gives rise to significant improvements in reducing FRR (False Reject Rate) and EER (Equal Error Rate).

key words: narrow swipe sensor, fuzzy c-means, fingerprint verification, minutiae descriptor, fingerprint template improvement

1. Introduction

Nowadays, fingerprint authentication technique has been widely applied in smart-phones, which is universally acknowledged to be an ideal method to protect private information from being divulged\[1\]. To embed fingerprint sensor into the smart-phone, the size of fingerprint sensor has to be reduced greatly. In this situation, narrow swipe sensor is particularly applicable due to relatively smaller physical volume. However, the size of image captured by narrow swipe sensor is much smaller than that captured by the conventional area sensor as shown in Fig. 1. This may lead to that the enrolled template image cannot cover the input fingerprint images with large displacement. In this regard, high FAR (False Accept Rate) becomes one of the most serious problems. Additionally, there is no space left for swiping-guide. As a result, the fingerprint image with non-linear distortion will be generated during the swiping process.

Conventional solutions for solving the limited sensing area problem are mainly divided into two kinds of approaches:

1. Image mosaicking, which combines multiple impressions at the image level\[2\]–[6].
2. Template feature synthesis, which merges feature from multiple impressions at feature level\[7\]–[11].

As for image mosaicking, A. Jain and A. Ross merged multiple fingerprint images by employing the iterative closest point (ICP) algorithm\[4\]. A. Ross et al. performed mosaicking by utilizing a thin plane spline as a transformation model to combine several fingerprint images to one template\[5\]. However, it is too computation-expensive to process multiple images for embedded system. Additionally, the mosaicked result is quite sensitive to the distortion and scaling.

As for the template feature sets synthesis methods, W.C. Ryu et al. employed the successive Bayesian estimation method to merge several enrollment minutiae sets\[10\]. T. Uz et al. merged several impressions based on the hierarchical Delaunay triangulations\[11\]. Nevertheless, compared to area sensor case, the distortion and scaling problems are more serious in the narrow swipe sensor situation. Furthermore, the image captured from narrow swipe sensor could be rotated or distorted by user’s swiping behavior. If we take the distortion and scaling issues into account, the traditional approaches might generate inferior template and also lower the system performance. Besides the two kind of methods mentioned above, S. Sin et al. updated a nine-templates structure during verification\[12\], however multiple templates dramatically increased the matching time and also the storage requirement.

In this work, we attempt to explore a convincing solution: a novel feature synthesis scheme to solve the non-linear distortion and scaling problems, thereby expanding the template coverage in narrow swipe sensor case. This scheme consists of two consecutive modules: 1) Registration Pattern Inspection (RPI) and 2) a novel Modified Fuzzy
C-Means (MFCM) cluster algorithm. Actually, the proposed two modules are closely interrelated, since the second module relies on the first module to ensure the synthesis candidates quality.

In the first module, synthesis candidates with serious non-linear distortion are eliminated. Based on a large amount of experimental data, we find that, if the user swipe over the sensor in an improper way, the distortion will be appeared in the reconstructed image. To model and address the distortion problem, a continuous vector representation of the swipe pattern: trajectory is derived from image reconstruction process. The trajectory directly describes the swiping behavior of human being. By utilizing this feature, the large distorted images could be rejected in advance even without image quality assessment. Consequently, the following cluster module will not suffer from distortion problem.

The second module is used to neutralize the scaling issue and eliminate the spurious minutiae, which can severely affect the matching performance. The proposed method is inspired by the following two aspects. (1) Minutiae descriptor has been validated to be an effective feature to represent fingerprint and to fulfill the matching tasks [13]–[23]. Generally, minutiae descriptor based methods perform much better than those based on minutiae in verification tasks, since the descriptors contains more information than a single minutia. In other words, the representation ability of standard minutia is enhanced by the auxiliary information from descriptor. (2) Motivated by the fact that fuzzy c-means (FCM) with its derivatives have been successfully applied in many classification tasks [24]–[28], in this work we employ the improved FCM algorithm to classify the minutiae descriptors from multiple impressions into several separated clusters. The statistical information derived from each cluster is applied to compensate the scaling issue, eliminate the spurious, and enhance the robustness of synthesized feature. The original FCM algorithm does not take any contextual information into consideration resulting in low robustness to noise. Response to this, in our approach the minutiae descriptor similarity constraint is incorporated intrinsically into the clustering process by supplementing a penalty term. Finally, the wider final template is obtained by merging each minutiae descriptor clusters. Furthermore, the unstable minutiae will be eliminated and the position of minutiae will be rectified as well. Experiments conducted over database, which is composed of narrow fingerprint images, approved the effecteness and robustness of proposed synthesis scheme.

The rest of this paper is organized as following: Sect. 2 presents the RPI algorithm. The minutiae descriptor is introduced in Sect. 3. Section 4 describes the MFCM clustering algorithm. Section 5 exhibits the experimental results and analysis to confirm the validity and robustness of the proposed method. A brief conclusion will be given in Sect. 6.

2. Registration Pattern Inspection

2.1 Narrow Swipe Sensor Image Reconstruction

In order to address the distortion issue, the image acquisition mechanism of the sweep sensor based system should be investigated, since it is significantly different from area sensor. Regarding the swipe sensor situation, the fingerprint image (as shown in Fig. 2(a)) need to be assembled from large amount of raw frames (as shown in Fig. 2(b)). This process is briefed as follows.

Firstly, a sequence of sampled raw image frames $\mathcal{F}$ are captured by the swipe sensor at a fixed sampling rate, which can be denoted as $\mathcal{F} = \{F_i\}_{i=0}^{K-1}$ where $F_i$ is a pixel matrix with dimensions of $N$ rows and $M$ columns. $K$ is the total frame count.

Secondly, By calculating the correlation of contiguous frames of $F_i$ and $F_{i+1}$, the corresponding horizontal displacement $\text{mvx}_i$ and vertical displacement $\text{mvy}_i$ are obtained which are denoted as the following.

$$\text{MV}_x = (\text{mvx}_0, \text{mvx}_1, \text{mvx}_2, \ldots, \text{mvx}_{K-2}, \text{mvx}_{K-1})^T$$
$$\text{MV}_y = (\text{mvy}_0, \text{mvy}_1, \text{mvy}_2, \ldots, \text{mvy}_{K-2}, \text{mvy}_{K-1})^T$$ (1)

where $\text{MV}_x$ and $\text{MV}_y$ are the continuous moving vector array.

Finally, by employing the $\text{MV}_x$ and $\text{MV}_y$, the redundant image lines are removed and then raw frames are reconstructed to a fingerprint image $R$ (as shown in Fig. 2(c)).

$$R = (L_0, L_1, L_2, \ldots, L_{H-2}, L_{H-1})^T$$ (2)

$L_i$ is the $i_{th}$ line from the reconstructed image $R$, which is represented in the matrix notation $L_i = (p_{i0}, p_{i1}, p_{i2}, \ldots$, }
Fig. 3  Distortion caused by swiping behavior of user. (a) Illustration of the instant swiping angel $\varphi_k$. (b-d) Instance of reconstructed fingerprint images. (b) The image with good quality. (c) The image with distortion. (d) The image with rotation. The corresponding swiping trajectory (e) with the distorted image (f).

Fig. 4  Illustration of swiping trajectory $T_K$ and instant swiping angel $\varphi_k$. (a) Instant swiping angel $\varphi_k$. $T_{W(k-1)}$, $T_W(k)$ and $T_{W(k+1)}$ denote three neighbouring sampling points with sampling window size $W$. (b) Generation of trajectory $T_K$ (red line) from moving vectors, the grey rectangles represent the captured raw image frames.

By utilizing the continuous vector array: $\text{MV}_x$ and $\text{MV}_y$, the characteristic of the user’s sweep behavior as shown in Fig. 3 (a) could be visualized and analyzed.

2.2 Registration Pattern Inspection

To quantify the distortion level, a continuous vector representation of the swipe pattern: trajectory $T_K$ is introduced. Figure 3 (b-d) illustrate the representative images with good quality and distorted ones. To formulate $T_K$, the moving vectors $\text{MV}_x$ and $\text{MV}_y$ are accumulated consecutively along horizontal and vertical direction and then turn out to be a series of key points. $T_K$ is defined by connecting those isolated key points with cascade lines as illustrated in Fig. 4 (b) and formulated by Eq. (4), Eq. (5) and Eq. (6).

$$x_k = \sum_{i=0}^{k} m\text{v}_{xi} \quad (4)$$

$$y_k = \sum_{i=0}^{k} m\text{v}_{yi} \quad (5)$$

$$T_K = \{(x_k, y_k)\}_{k=0}^{K-1} \quad (6)$$

where $m\text{v}_{xi} \in \text{MV}_x$ and $m\text{v}_{yi} \in \text{MV}_y$ are instant moving vectors, $x_k$ and $y_k$ are accumulated horizontal and vertical displacement, respectively. According to these equations, each horizontal displacement in raw frames is accumulated along the swiping direction. To this end, each tiny finger movement in the swipe process is recorded by the trajectory $T_K$. An example of distorted image with corresponding trajectory is shown in Fig. 3 (e and f). As a result, $T_K$ explicitly reflects the user’s sweep movement over the reconstructed image. After the trajectory $T_K$ is obtained, we use the standard deviation $SD(\varphi)$ of instantaneous swipe angles (as shown in Fig. 4 (a)) to describe the distortion level as de-
talled in Eq. (8). This is due to the fact that if the user swipe over the surface of the sensor with a uniform direction, the $SD(\varphi)$ would be equal to zero. In other words, if the user rotates the finger irregularly during the swipe procure, the reconstructed image is distorted along with large $SD(\varphi)$. As a result, the distortion level influenced by the user’s behavior can be approximately estimated by $SD(\varphi)$.

To simplify the computation process, the trajectory is equidistantly divided into $M$ partitions with fixed window size of $W$ and then the instantaneous swipe angle array $\{\varphi_k\}_{k=0}^M$ is derived from the trajectory $T_K$. Namely, the $\varphi_k$ is the relative angle of two consecutive partitions which could be calculated by Eq. (7).

$$
\varphi_k = \Gamma(\arctg(\frac{y_{W(k+1)} - y_{W(k)}}{x_{W(k+1)} - x_{W(k)}}), \arctg(\frac{y_{W(k)} - y_{W(k-1)}}{x_{W(k)} - x_{W(k-1)}}))
$$

(7)

where, $\Gamma(\theta, \varphi)$ denotes the rotation angle from $\theta$ to $\varphi$ and $W$ is the window size, $x_k$ and $y_k \in T_K$, respectively.

$$
SD(\varphi) = \sqrt{\frac{1}{M} \sum_{j=1}^{M} (\varphi_j - \mu_{\varphi})^2}
$$

(8)

$$
\mu_{\varphi} = \frac{1}{M} \sum_{j=1}^{M} \varphi_j
$$

(9)

To normalize the distortion level, score $S(\varphi)$ is defined as the following Eq. (10). As a result, the distortion score $S(\varphi)$ spreads between 0 and 1.

$$
S(\varphi) = e^{-SD(\varphi)/T_r}
$$

(10)

where $T_r$ is a normalization parameter. According to different values of the distortion score: $S(\varphi)$, the reconstructed images can be classified as follows:

1. Class I: Straight image without distortion;
2. Class II: Distorted image;
3. Class III: Rotated image without distortion.

In case that $S(\varphi)$ is larger than a predefined threshold $D_{thr}$, the candidate is considered as good quality (Class I and Class III). Note that $D_{thr}$ is derived from sufficient experimental observation. Consequently, the uniform swipe angle $\varphi$ can be simply estimated by $\mu_{\varphi}$, and the minutiae feature extracted from rotated image (Class III) could be compensated. After candidates filtering, the images in Class I and Class III are selected for the synthesis process.

3. Minutiae Descriptor

In this approach the minutiae descriptor is employed to facilitate the cluster process. This descriptor consists of two features: Minutiae Ridge Tracing Points (MRTP) and Minutiae Orientation Descriptor (MOD).

3.1 Minutiae Ridge Tracing Points

In our approach, a series ridge tracing points $R'$ are served as a representation of the corresponding ridge, where $i$ is the minutiae index. Two rotation invariant features, the Euclidean distance $RL_i$ and rotation angle $R\theta_i$ between two neighbor sampling points, are derived from ridge tracing points as follows:

$$
R' = \{R_{L_k}^i, R_{\theta_k}^i\}_{k=1}^{N_R}
$$

(11)

where $k$ is the tracing points index, $N_R$ is the total number of each ridge tracing points. An instance of MRTP is shown in Fig. 5 (a).

3.2 Minutiae Orientation Descriptor

The MOD is extracted by following procedures. (1) ROI (Region of Interest) definition. The circular area centering at minutia position, and ranging from radius $R_t$ to $R_o$ is served as the ROI. In our work, the $R_t$ is 10 pixels, while the $R_o$ is 40 pixels, respectively. (2) Tessellation. We circularly tessellate the ROI area into equidistant sectors and bands,
which is denoted as \( S = \{S_{n}\}^{n=1}_{n=s}\) where \( s \) is the sector count and \( b \) is the band count, \( n \) is the sub-sector index. The red circular area in Fig. 5 (b) is an example of band, while the blue area shows one sub-sector \( S_{n}\). In this figure, there exists 3 bands and each band consists of 8 sectors. Of note, the first band starts from the minutia direction to achieve rotation invariant. (3) Orientation calculation. The descriptor can be denoted as follows:

\[
MO^{i} = \{\omega^{i}_{k}\}^{k=1}_{k=1}
\]

(12)

where \( \omega^{i}_{k} \in [0, \pi) \) are the corresponding orientation sets derived from the circular tessellation \( S \), \( i \) indicates that the descriptor belongs to the \( i_{th} \) minutia. In our experiments, the \( s \) is selected as 8 and \( b \) is set to be 3, respectively. An instance of tessellation result is shown in Fig. 5 (b). (4) Prediction. In the narrow swipe sensor case, the ROI easily falls outside the foreground region, which will be considered as invalid area. To address this issue, we predict the orientation value \( \psi_{i} \) of invalid sector from its \( N_{O} \)-nearest valid cells, as shown in Fig. 5 (c) by Eq. (13):

\[
\psi_{i} = \frac{1}{2} \arctg \left( \frac{\sum_{o=1}^{O} \sin 2\omega_{o}}{\sum_{o=1}^{O} \cos 2\omega_{o}} \right)
\]

(13)

where \( \psi_{i} \) is the predicted orientation value, while \( \{\omega_{o}\}^{N_{O}}_{o=1} \) are orientation of its nearest neighbors.

4. Cluster Minutiae Descriptors by Modified FCM

4.1 Template Synthesis by MFCM

The MFCM synthesis process is detailed as follows. Firstly, the prime template is selected from several enrolled fingerprint candidates by examining the distortion score and image quality.

Secondly, the core point which consists of coordinate \( x \) and \( y \) in pixels is extracted. Note that for the arc type fingerprint, the point with highest curvature in the ridge, is assigned as the core point. The core extraction algorithm in [29] is used in this work.

Thirdly, all the qualified input fingerprints are aligned with the prime template by the core position. The qualified inputs are defined as follows: 1) Matching score against prime template is higher than the threshold \( S_{thr} \).

The minutiae descriptor based greedy matching algorithm in [18] is applied to get the matching score. Furthermore, we use the Eq. (19) and Eq. (20) to obtain the similarity of one minutia descriptor pair. The final matching score of a pair of fingerprint images is normalized to \([0, 1000]\) in our work. 2) Distortion score is higher than \( D_{thr} \). In our experiments the \( S_{thr} \) is selected as 600 out of 1000, while the \( D_{thr} \) is selected as 0.8 out of 1.0.

We also notice that the robustness of extracted minutiae descriptor set and core also have significant impact on the performance of proposed synthesis algorithm. To specific, the inferior image quality can increase the possibility of spurious appearance and lower the accuracy of core detection result. Responding to this, we employ an image quality map to select robust minutiae and core according to the quality assessment. Firstly, a block-wise (e.g. \( 16 \times 16 \) pixels for one block) quality index as shown in Fig. 6 (a and b) is derived from the original image. We use the strength of average squared binary gradients which is introduced in [30] to calculate the block-wise image quality value. Secondly, the quality map is binarized with respect to the threshold as shown in Fig. 6 (c) which only consists of black and white blocks. Finally, the minutiae located in the black block are selected for the synthesis process. The candidates, whose core is located at white block region, are eliminated. Since we select the candidates with strict quality regulation, the core feature could be considered as a robust landmark for alignment.

Finally, the minutiae descriptors are clustered by MFCM and then the clusters are merged by predefined rules followed by that new minutiae are added into the prime template. The overall flowchart of proposed synthesis scheme is illustrated in Fig. 7.

4.2 Fuzzy C-Means Clustering Algorithm

FCM clustering algorithm, an unsupervised clustering technique, has been widely used in classification applications. The algorithm iteratively clusters the data set to an optimal \( c \) partitions by minimizing the squared error objective function \( J_{m} \) by the following equation:

\[
J_{m} = \sum_{k=1}^{c} \sum_{i=1}^{N_{r}} u_{k}^{m}||x_{i} - v_{k}||^{2}
\]

(14)

where \( X = \{x_{i}, i = 1, 2, \ldots, N| x_{i} \in \mathbb{R}^{d}\} \) is the data set in the \( d \)-dimensional vector space, \( c \) denotes the number of clusters, \( N_{r} \) is the number of points in the data set. \( u_{k} \) describes the degree of membership of \( x_{i} \) in the \( k_{th} \) cluster, \( m \) is a fuzzy
Fig. 7 A schematic illustration of proposed synthesis method. (a) The aligned and accumulated minutiae descriptors. The red lines are accumulated minutiae descriptors (note that, only minutiae ridge tracing points are drawn on the image), the black lines are the minutiae descriptor from the prime template. (b) Showing the MFCM result, different colours indicate different clusters. (c) Merging the minutiae clusters, and combining with the prime template.

4.3 Modified FCM Clustering Algorithm

Intuitively, the minutiae descriptors can be considered as some points distributed on the coordinate plane. Our target is to classify those points into \( c \) clusters with respect to their position and intrinsic feature. In this work, the position refers to the coordinate of minutia descriptor \( \{x_i, y_i\}_{i=1}^{N_D} \), and the descriptor \( \{R^i, MO^i\}_{i=1}^{N_D} \) describe the intrinsic characteristic of minutia, where \( N_D \) denotes the aligned minutiae number. We extend the original FCM by incorporating the minutiae descriptor similarity into the objective function.

\[
J_{MFCM} = \sum_{k=1}^{c} \sum_{i=1}^{N_D} u_{ki}^m \left( \frac{\|x_i - v_k\|^2}{\sum_{k=1}^{c} \sum_{i=1}^{N_D} S M_{rk}^2} \right) \quad (15)
\]

where \( v_k \) and \( u_{ki} \) are defined as follows:

\[
v_k^{(b)} = \frac{\sum_{i=1}^{N_D} (u_{ki}^{(b)})^m x_i}{\sum_{i=1}^{N_D} (u_{ki}^{(b)})^m} \quad (16)
\]

\[
u_{ki} = \frac{1}{\sum_{j=1}^{c} \left( \frac{\|x_i - v_j\|}{\sum_{i=1}^{N_D} S M_{ji}} \right)^{1/m-1}} \quad (17)
\]

where \( D_R \) is the neighborhood minutiae descriptors set within block-size \( R \) by \( R \). \( n_R \) is the overall minutiae descriptor number in the neighborhood block. \( \xi \) controls the strength of influence from neighborhood descriptors. \( r \) represents one of the neighbor minutiae descriptors of cluster prototype descriptor \( k \). \( b \) is the loop counter. \( S M_{rk} \) is the similarity between minutiae descriptor \( r \) and cluster prototype descriptor \( k \). \( x_i \) and \( y_i \) are the coordinates of the minutiae descriptor which consists of \( x \) and \( y \). \( S M_{rk} \) is formulated by the following equation:

\[
S M_{rk} = \alpha S_R(r, k) + \beta D_{MO}(r, k) \quad (18)
\]

where \( S_R(r, k) \) and \( D_{MO}(r, k) \) are the similarity measurement function (Eq. (19) and Eq. (20)) of minutiae ridge tracing points and orientation descriptor, respectively. \( \alpha \) and \( \beta \) are the weights assigned to each part, respectively. In our experiments, the \( \alpha \) is set to be 0.8 and the \( \beta \) is set to be 0.2.

\[
S_R(r, k) = \frac{1}{N_R} \sum_{m=1}^{N_R} \exp \left( \epsilon_1 |RL^m_r - RL^m_k| \right) + \epsilon_2 d(R^m_r, R^m_k) \quad (19)
\]

where \( N_R \) is the common tracing points number of corresponding minutiae pair. \( \epsilon_1 = 0.4 \) and \( \epsilon_2 = 0.6 \) are the weights of each contribution.
$$D_{\text{MO}}(r,k) = \left( \sum_{n=1}^{\text{c}} \left( \cos 2\omega_r - \cos 2\omega_k \right)^2 \right)^{1/2}$$

(20)

The MFCM algorithm is described in the following.

Step 1. Initialize the membership matrix $U = [u_{ki}]_{1 \leq k \leq c, 1 \leq i \leq N}$ with random values between 0 and 1 and also satisfy the constraint $\sum_{k=1}^{c} u_{ki} = 1, i = 1, 2, \ldots, N$. Since the spurious minutiae clusters could be eliminated by the merging step, the clusters number $c$ is decided by the maximum number count of aligned minutiae from synthesis input. Note that, we initialize the cluster centroids $V_k$ by randomly selected minutiae. Empirical setting of neighbour block size $R$ to 32 pixel.

Step 2. Update the cluster center $\{v_k\}_{k=1}^{c}$ by Eq. (16).

Step 3. Update the membership matrix $u_{ki}$ by Eq. (17).

Step 4. The objective function can get minimum as follows: when $\|V_{\text{new}} - V_{\text{old}}\| < \epsilon$, the iteration will be terminated accompanied with generating $c$ partitions, where $V$ is the cluster center vectors. The value of $\epsilon = 10^{-3}$ is found to be appropriate by large amount of experiments.

4.4 Merging Minutiae Descriptor Clusters

By employing the statistical information derived from the minutiae cluster, new minutiae position is decided by the corresponding cluster center, and also spurious minutiae are eliminated. The rule to examine the spurious minutiae is that the ratio of member count of a cluster to the average member count is less than 0.38. In this situation this cluster would be eliminated.

5. Experimental Results

5.1 Experiment Environment

In our experiments, the accuracy and robustness of the proposed algorithm are evaluated. The database is captured by a swipe sensor named FPC1080. The physical width of the swipe sensor is only 8 mm, covering approximately half width of normal human finger, and the width of generated raw image is 126 pixels in this system. The height of the reconstructed image is approximately 400 pixels. The original raw image frames are reconstructed firstly, then the fingerprint image and corresponding moving vectors are used for evaluation. The database consists of 100 fingers, where each finger includes 100 images. Figure 2 shows an example image of the database. Note that, the images with non-linear distortion and bad quality region are included in this database.

False Accept Rate (FAR), False Reject Rate (FRR) and Equal Error Rate (EER) are commonly used to estimate the performance of a fingerprint identification system. The FAR is calculated by the probability that imposter impressions are falsely accepted, on the other hand FRR is calculated by the probability that the genuine impressions are falsely rejected. Therefore, the FAR is considered as the measurement on security while FRR is the measurement on convince. DET (Detection Error Tradeoff) curve plots the FRR against the FAR at different thresholds. FAR100, FAR1000 and FAR10000, which denotes the value of FRR for FAR equals 1/100, 1/1000, 1/10000, respectively.

5.2 Evaluation of Registration Pattern Inspection

In order to validate the performance gained by the proposed RPI algorithm, two experimental results are compared. The first one is conducted with the templates selected by RPI. The image with highest distortion score is assigned as the template. The second one is conducted by randomly selecting templates, and matching against the same testing set. In order to evaluate the algorithm more objectively, we randomly select 10 sets of the original templates from candidates and calculate the mean and standard deviation of the EER and FAR values, respectively. The minutiae descriptor based greedy matching algorithm in [18] is applied to get the matching result.

The database is divided into two groups, the first 30
images of each finger are served as the template candidates, while the rest 70 images are used for matching. Therefore, the number of genuine matching is $100 \times 70 = 7000$, and the number of imposter matching is $100 \times (100-1) \times 70 = 693000$. The experimental procedures are shown as Fig. 8. Comparison results for with RPI and without RPI, are illustrated in Fig. 9. The results suggest that the performance is significantly improved by proposed RPI algorithm. The mean value of EER of ten tests decreases from 6.28\% to 2.75\%, and FAR10000 value decreases from 17.70\% to 8.25\% as detailed in Table 1. Based on our experiments, there are approximately 12 qualified inputs for each finger in average. This result could be interpreted that the templates candidates with non-linear distortion are removed by
RPI algorithm. The templates with better quality significantly contribute to the performance gain. This result also indicates that the quality of templates has strong impact on the verification performance. Several instances of images which from the same finger with respective distortion score are shown in Fig. 10. Note that, larger value indicates less distortion appears in the fingerprint images.

5.3 Evaluation of MFCM

In order to evaluate the synthesis algorithm, we compare three results: (1) the matching results by utilizing the MFCM plus RPI; (2) the matching results by utilizing the RPI; (3) the matching results by utilizing the original templates. We use the images selected by RPI as the prime templates, then the synthesis process exhausts all the training set to generate the final template. Finally, we check the performance gain by proposed MFCM algorithm. The minutiae descriptor based greedy matching algorithm in [18] is used to get matching results. The detailed results are shown in Table 1. The DET curves of comparison results are illustrated in Fig. 9. From the DET curves we can see that, the random tests yield the lowest performance due to distortion and small coverage area. When the RPI filter the template candidates, the EER value drops from 6.28% to 2.75%. Finally, by applying the proposed synthesis scheme with 30 candidates, EER decreases from 2.75% to 1.51%, and FAR10000 decreases from 8.25% to 4.90%, respectively. These results confirm that the performance has been dramatically improved with the benefits of robustly expanded templates. To specific, we further explain these results by following two aspects. Firstly, the expanded template coverage brings up the genuine matching score. The Fig. 11 shows the average template coverage at different merging times. Upon exhausting 30 candidate impressions, the average template coverage is expanded from 126 pixels to 176 pixels and also the average minutiae number is increased from 14 to 28 as well. Secondly, the template feature is refined by the proposed MFCM algorithm, minutiae position and descriptor are refined with higher precision and spurious minutiae are eliminated. According to examples of cluster centroids and cluster members as shown in Fig. 12, it is obvious that the orientation descriptor of cluster members has similar ridge flow patterns as their corresponding cluster centroids. This result confirms the validity of the descriptor based cluster algorithm. The maximum memory required by this method is less than 20k words which allows the algorithm could run in an embedded system. Additionally, the processing speed is approximately 10 milliseconds in a 2.8 GHz Quad-core PC.

5.4 Algorithms Evaluation

Since almost all the fingerprint template synthesis algorithms are targeting at area sensor case, we compare our work with Sin’s template update method[12] which is designed for narrow swipe sensor same as our method.

The same training and matching set are applied, then the matching results are compared. The DET curves are shown in Fig. 13 and detailed in Table 2. The EER drops from 2.52% to 1.51%, while the FAR10000 drops from 10.2% to 4.90%. Since the method in [12] did not take the
Fig. 14  The synthesis results. (a) The first column are original prime templates. (b) The second column are extracted minutiae with associated tracing points. (red line). (c) The third column are accumulated minutiae descriptors (note that, only minutiae ridge tracing points are drawn on the image), the black lines are the minutiae descriptor from the prime template. The red lines are accumulated minutiae descriptors. (d) The fourth column are cluster results. Different colours indicate different clusters. (e) The last column are merging results, and combine with prime template. The black rectangle indicates the eliminated minutiae cluster.
Table 2  Comparison results of proposed method and method from [12]

<table>
<thead>
<tr>
<th>method</th>
<th>Template size</th>
<th>Matching time</th>
<th>EER(%)</th>
<th>FAR1000(%)</th>
<th>FAR10000(%)</th>
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<tbody>
<tr>
<td>Sin [12]</td>
<td>6K bytes</td>
<td>60ms</td>
<td>2.52</td>
<td>7.41</td>
<td>10.2</td>
</tr>
<tr>
<td>Proposed</td>
<td>3.8K bytes</td>
<td>10ms</td>
<td>1.51</td>
<td>2.86</td>
<td>4.90</td>
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</tbody>
</table>

Table 3  Comparison results of proposed algorithm and the algorithms in [13], [16], [21] and [23].

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>EER(%)</th>
<th>FAR100(%)</th>
<th>FAR1000(%)</th>
<th>FAR10000(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratha [13]</td>
<td>3.66</td>
<td>5.16</td>
<td>9.33</td>
<td>15.66</td>
</tr>
<tr>
<td>Chikkerur [16]</td>
<td>2.73</td>
<td>3.41</td>
<td>7.84</td>
<td>12.51</td>
</tr>
<tr>
<td>Choi [21]</td>
<td>2.10</td>
<td>2.78</td>
<td>5.06</td>
<td>9.49</td>
</tr>
<tr>
<td>Zhou [23]</td>
<td>1.95</td>
<td>2.38</td>
<td>3.75</td>
<td>5.57</td>
</tr>
<tr>
<td>Proposed</td>
<td>1.51</td>
<td>1.75</td>
<td>2.86</td>
<td>4.90</td>
</tr>
</tbody>
</table>

Fig. 15  DET curves of proposed method and methods in [13], [16], [21] and [23].

The distortion issue into consideration, the distorted images are easily enrolled as template, and thus, the verification accuracy would be compromised. Furthermore, Sin employed multiple templates to form the template structure which is computation expensive to get matching result. Thanks to the RPI module and synthesis module, our method achieves lower EER and FAR10000 value than that obtained by Sin’s method. Furthermore, the final template size in our method is almost half of that in Sin’s method. Thus our synthesis scheme is a more compact and effective method. Additionally, the matching time drops from 60 milliseconds to 10 milliseconds compared with Sin’s method. Figure 14 shows several synthesis instances by MFCM, the spurious minutiae marked by black rectangle are eliminated.

We also compare our proposed technique with four well-known minutiae descriptor based approaches.

1. Ratha [13]- fixed-radius minutiae descriptor.
2. Chikkerur [16]- nearest-neighbours based minutiae descriptor.

The DET curves of comparison results are shown in Fig. 15. The corresponding algorithm performance indices (EER and FAR) of four methods [13], [16], [21], [23] and proposed algorithm are reported in Table 3. One can see that our proposed method achieves the lowest EER value. This result can be explained as follows: (1) The local minutiae neighbour based method [13] and [16] suffered from limited minutiae number in narrow fingerprint situation. (2) The method in [21] and [23] employed the ridge feature and texture information around minutiae to increase the discrimination power, respectively. However, they both suffered from border effect in narrow fingerprint case. (3) By employing the refined minutiae descriptor obtained from proposed MFCM algorithm, our method outperforms the above four approaches. In other words, the template feature representation becomes more accurate by employing the MFCM.

6. Conclusions

In this work we employ a novel minutiae descriptor based synthesis algorithm to generate an expanded new template for narrow swipe sensor based system. Our major contributions can be summarized as follows: (1) A novel user behavior based distortion analysis algorithm: RPI is proposed, to quantify the distortion level in the reconstructed image of narrow swipe sensor. The candidates containing non-linear distortion could be removed in advance without time-consuming image quality check. The candidates containing non-linear distortion could be removed in advance without time-consuming image quality check. The candidates containing non-linear distortion could be removed in advance without time-consuming image quality check. The candidates containing non-linear distortion could be removed in advance without time-consuming image quality check. (2) A minutiae-descriptor based cluster algorithm MFCM is proposed, which works robustly to deal with the scaling issue, eliminate spurious minutiae, and generate the expanded template. By applying the proposed method, the matching accuracy is improved without sacrifice of the compactness of template. Moreover, the matching time is dramatically decreased compared with multiple templates based approach. These results demonstrate the feasibility of obtaining a very effective fingerprint template representation for narrow sensor based fingerprint authentication systems. These results also encourage further exploitation of the matching method for distorted image caused by the user’s behavior.

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