Journal of Scientific & Industrial Research
Vol. 79, March 2020, pp. 201-208

Segmentation Techniques through Machine Based Learning for Latent Fingerprint Indexing and Identification

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Received 7 November 2019; revised 15 November 2019; accepted 19 January 2020

Latent fingerprints have become most important evidence in law enforcement department and forensic agencies worldwide. It is also very important evidence in forensic applications to identify criminals as it is mostly encountered in crime scenes. Segmentation is one of the solutions to extract quality features. Fingerprint indexing reduces the search space without compromising accuracy. In this paper, minutiae based rotational and translational features and a global matching approach in combination with local matching is used in order to boost the indexing efficiency. Also, a machine learning (ML) based segmentation model is designed as a binary classification model to classify local blocks into foreground and background. Average indexed time as well as accuracy for full as well as partial fingerprints is tabulated by varying the template sminutiae.

Keywords: Average Indexed Time, Global Structure Matching, Gradient, Machine Learning, And Translational Features

Introduction

Fingerprints have been widely used in both civilians and law enforcement applications to determine the identity of an individual or to verify someone's claimed identity. However, latent fingerprints are left behind the surface when something is touched or handled. Complex chemical process is used to lift the latent fingerprints from the surface[3]. Fingerprints obtained using different types of techniques. Latent fingerprint were first introduced to the world as an evidence to convict a suspect in Argentina in 1893. Since then, it has become most important evidence in law enforcement department and forensic agencies worldwide[4]. They are also very important evidence in forensic applications to identify criminals as it is mostly encountered in crime scenes. Rolled and plain fingerprints also collectively called exemplars which means known, are good quality fingerprints collected under the supervision of expert, either for the purpose of enrolment in a system or when the suspects under arrest. The objective of the fingerprint verification systems is to focus on matching the query fingerprint of a person with the templates stored in the dataset[1]. Usually, the verification system works on one to one comparison basis. Since, this model is used for the validation therefore the speed of this system depends on the number of templates stored in the dataset.

(i) Accuracy is poor due to non-differentiable features and
(ii) Alignment is not robust

Generally, minutiae features based fingerprint indexing algorithms are commonly used[4] which extract a set of translational and rotational features from minutiae points. However, local minutiae structures in query fingerprint lead to high similarity score with non-mated template fingerprints. In this paper, minutiae based rotational and translational features and a global matching approach in combination with local matching is used in order to boost the indexing efficiency[3]. The proposed indexing algorithm works as a two way process:

(i) Formation of subset of candidates using local matching approach and
(ii) Global matching with selected subset of candidates.

Segmentation

Many methods proposed in the past to segment the normal fingerprint images[5]. These methods are based on local features of blocks $w \times w$ such as mean,

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variance, and orientation consistency to evaluate the quality of fingerprint for segmentation. These approaches can work well with normal fingerprints, however their performance are not satisfactory for latent fingerprints[2]. The main difficulties in segmenting latent fingerprints using these methods are due to: poor ridge clarity, background noise, partial impression of fingerprint, structured marks and many more[3]. Thus segmentation of latent fingerprints is still challenging and active research area. Many new methods have been developed[7] to improve the latent fingerprint segmentation. But this model is suitable for decomposing textures with orientation patterns. In 2016 also A. Shankarn *et al.*[2] proposed features selection and learning based latent fingerprint segmentation model. They have considered fingerprint related features of local block of size $w \times w$. Figure-1. They have obtained features based on saliency, image intensity, ridge, and quality. Therefore, in total their model calculates 23 features of every local block $w \times w$, however the model is biased towards features as the optimal features for all datasets NIST SD4, NIST.

Features Extraction

In order to classify whether a block of size $w \times w$ contains fingerprint patterns require fingerprint related features such as gradient, ridge etc. In this paper three different categories of features are calculated which can be used to differentiate finger print regions with non-fingerprint regions.

(i) Features based on gradient(ii) Features based on ridge and (iii) Features based image intensity

Features based on gradient

The directional change in pixel intensity is obtained using gradient. Therefore, this change will be more regular in fingerprints region than non-fingerprints or noisy region. Gradient of an image can be used for orientation estimation of ridges in local block and good features to differentiate the latent fingerprint from the background. The orientation at a point (i,j) can be calculated as:

$$Orientation(i,j) = \begin{cases} \pi/4, G1 = 0, G2 < 0 \\ 3\pi/4, G1 = 0, G2 \geq 0 \\ \theta(i,j) + \pi/2, G1 > 0 \\ \theta(i,j), G1 < 0, G2 \leq 0 \\ \theta(i,j) + \pi, G1 < 0, G2 > 0 \end{cases} \quad \ldots (1)$$

Where, $\theta(i,j)$, G1, and G2 are defined as follows:

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{G2}{G1}\right) \quad \ldots (2)$$

$$G1 = \sum_{i=1}^{w}\sum_{j=1}^{w}(I_x^2(i,j) - I_y^2(i,j)) \quad \ldots (3)$$

$$G2 = \sum_{i=1}^{w}\sum_{j=1}^{w} 2 * I_x(i,j) * I_y(i,j) \quad \ldots (4)$$

I_x, I_y are the gradient along x and y direction respectively.

Once, the orientation are calculated then the features based on gradient can be calculated as:

(i) Ridge orientation: It can be calculated using Gaussian smoothing kernel [9].

$$ROF = \frac{1}{w^2}\sum_{i=1}^{w}\sum_{j=1}^{w} Orientation'(i,j) \quad \ldots (5)$$

$$Orientation'(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\sin(2Orientation(i,j)) * G(i,j)}{\mathrm{cost}(2Orientation(i,j)) * G(i,j)}\right) \quad \ldots (6)$$

Where, $G(i,j)$ is the Gaussian smoothing kernel.

(ii) Squared gradient sum: The interleaving ridge-valley pattern provides a change in flow which will be maximum in fingerprint region than background or noisy region. This interleaving ridge-valley pattern can be calculated using the squared gradient sum and can be obtained using equation (7).

$$SGSF = \sqrt{G_1^2 + G_2^2} \quad \ldots (7)$$

(iii) Sum of norm of squared gradient:

$$SNSDF = \sum_{i=1}^{w}\sum_{j=1}^{w}(I_x^2(i,j) - I_y^2(i,j))^2 + (2 * I_x(i,j) * I_y(i,j))^2 \quad \ldots (8)$$

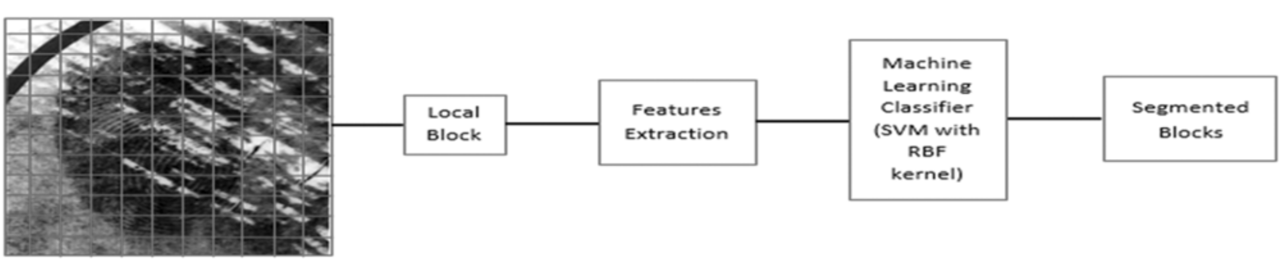

Fig. 1 — Latent fingerprint segmentation approach

Features based on ridge

Three different features based on ridge can be calculated to differentiate the latent fingerprint from many noisy patterns belonging to other fingerprints in the background.

(i) ***Ridge frequency:*** This feature can be calculated by applying Fourier transformation to each $w \times w$ local block using equation (9)

$$RF = argmax\left(\sum_{i=1}^{w}\sum_{j=1}^{w}|X(i,j)| * F_k(i,j)\right)$$

Where, $|X(i,j)|$ is the Fourier transformation of local image blocks and $F_k(i,j)$ is the kth directional filter. Frequency of the filter gives maximum response is considered as ridge frequency.

(ii) ***Inter-ridge average distance:*** Fingerprint region contains higher number of ridges, therefore the inter-ridge average distance would be minimum as compared to non-fingerprint region. Inter-ridge average distance can be calculated using equation (10).

$$IRAD = \frac{\sum_{l=1}^{P} D_l}{P-1} \quad \dots (10)$$

Where, P is the number of ridges peaks and D_l is the consecutive peak distance.

(iii) ***Variance of peak heights in ridges:*** Variance in ridge pressure in $w \times w$ block size can be computed using equation (11)

$$VPR = \frac{\sum_{l=1}^{P}(Peak_l - Peak_{mean})}{P-1} \quad \dots (11)$$

Where, $Peak_l$ is the ridge height of l^{th} peak and $Peak_{mean}$ is the average ridge height of all peaks across all blocks.

(iv) ***Energy of the ridge:*** This energy feature provides the "ridgeness" of the local block of size $w \times w$ and expected to be more in fingerprint region than non-fingerprint region. The "ridgeness" of the local block acts a measure of confidence and is very helpful in latent finger print segmentation. The energy of the ridge can be calculated using equation (12) as follows:

$$EOR = \frac{1}{w^2}\left(\sum_{i=1}^{w}\sum_{j=1}^{w}(|X(i,j)| * F_k(i,j))^2\right) \quad \dots (12)$$

Features based on image intensity

Three different intensity based features are calculated in this paper to support the classifier better classify between foreground and noisy background. Features based on image intensity are as follows:

(i) Difference between local and global mean:

This feature calculates the difference between local and global mean. Since, global mean the mean of the complete image which must be close to average grayscale value. However, the local mean or the mean of the pixels in local block would also be close to grayscale value for fingerprint patterns as compared to noisy background. Therefore, the value of this features give lower value for fingerprint region. This feature can be calculated using equation (13)

$$LGMD = \left(\frac{1}{w^2}\sum_{i=1}^{w}\sum_{j=1}^{w} I(i,j)\right) - I_{mean} \quad \dots (13)$$

Where, I_{mean} is the average intensity of complete image and $I(i,j)$ is the intensity at pixel location (i,j)

(ii) Local variance:

This feature calculates the variation of intensities in local block of size $w \times w$. Due to interleaved ridge-valley structure, the variance in fingerprint region would be more as compared to noisy background. The local variance can be calculated using equation (14).

$$LV = \frac{1}{w^2}\sum_{i=1}^{w}\sum_{j=1}^{w}\left(I(i,j) - \frac{1}{w^2}\sum_{i=1}^{w}\sum_{j=1}^{w} I(i,j)\right)^2 \quad \dots (14)$$

(iii) Local ridge pixels clustering:

Properties of both mean and variance are combined by this feature to capture the ridge valley structure in fingerprints. It is basically the clustering between ridge pixels. This feature can be computed using equation (15)

$$LRPC = \sum_{i=1}^{w}\sum_{j=1}^{w} Y1(i,j) \times Y2(i,j) \quad \dots (15)$$

Where

$$Y_1(i,j) = \begin{cases} 1 \text{ if } I(i,j) < I_{mean} \\ 0 \text{ otherwise} \end{cases}$$

$$Y_2(i,j) = \begin{cases} 1 \text{ if } Y(i,j) < \left(\frac{w^2}{2} + 1\right) \\ 0 \text{ otherwise.} \end{cases}$$

$$Y(i,j) = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}}\sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} Y_1(u,v)$$

Here, Y is the degree of uniformity in a local block of size $w \times w$ and it tends to be larger in uniform background regions than in ridge valley regions.

Features vector of the local block of size $w \times w$ wouldbe

$[ROF, SGSF, SNSDF, RF, IRAD, VPR, EOR, LGMD, LV, LRPC]$

Classification using machine learning methods

The role of machine learning algorithms is to classify each block into foreground and background on the basis of features calculated above. A non-linear classification algorithm, Support Vector Machine (SVM) is used in this paper[8]. Step by step approach for development of machine learning model is discussed below.

1. Dataset Preparation- For experiment latent fingerprint dataset[7] is used.
2. Split the data into training and testing sets- We developed 1000 positive and 1000 negative samples of size $w \times w$. The positivesamples contain normal fingerprint as well as latent fingerprint images, while negative samples contain non-fingerprints.
3. Development of feature set and labelling them as 1 (foreground) and 0 (background)- Once the features are constructed then every feature vector would assign a label as1 or 0 so that machine learning model would differentiate between foreground and background during training and develop optimum boundary between these two.
4. Training of machine learning models- Machine learning model would be trained with the help of feature set and their labels
5. Testing- Once the model is trained then it can be used to predict the block into foreground and background on the basis of prediction of model. If prediction of a local block is 0 then it would be background else foreground.

Local and Global Matching Approach for Fast Latent Fingerprints Indexing

Global structure of the fingerprints and the local structure of the minutiae are used in this paper for fingerprint minutiae matching. This matching algorithm is inspired by the manual verification process of human expert and is proposed by Jiang *et al*.[8]. Usually, human expert examine the local and global structure of the minutiae to validate the fingerprint. This approach automates the human expert behavior. Since, local structure represents a small portion of the fingerprint, therefore it can tolerate reasonable amount of distortions present in latent fingerprints. The advantage of this matching algorithm is that it is independent from the translational and rotational dependency, fast, accurate, and distortion resistant.

Local structure matching

A minutiae point P_i detected from a fingerprint can be defined by a feature vector as:

$$F_i = (x_i, y_i, \varphi_i)$$

Where F_i is the feature vector of i^{th} minutiae, (x_i, y_i) is its coordinates and φ_i is the direction of local ridge. Set of all feature vector **FV**, which consists of features of all minutiae $i = 1,2,3, \dots\dots, N$ obtained from a fingerprint forms a global minutiae structure. The minutiae matching algorithm is used to find the level of similarity between global minutiae structure of input fingerprint and the template fingerprints. The global characteristics of the minutiae x_i, y_i and φ_i having translational and rotational dependency of fingerprints.

The features can be formed by calculating the distanceD_{ik}, radial angleθ_{ik}, and minutiae direction φ_{ik} from minutiae P_i to its k-nearest neighborsP_k. The feature vector of minutiae P_i to its k-nearest neighbours P_k thus formed as:

$$MFV_k^i = (D_{ik}, \theta_{ik}, \varphi_{ik})$$

Where,

$$D_{ik} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}$$

$$\theta_{ik} = del\emptyset \left\{ \tan^{-1}\left(\frac{y_k - y_i}{x_k - x_i}\right), \varphi_i \right\}$$

$$\varphi_{ik} = del\emptyset(\varphi_i, \varphi_k)$$

Generally, the range of ridge orientation is $(-\frac{\pi}{2}, \frac{\pi}{2}]$, therefore to increase the discrimination it has been re-directed into the range $(-\pi, \pi]$. The $del\emptyset$ function used above is used to transform the range. The function for the difference between two directions θ_1, θ_2 can be defined as follows:

$$del\emptyset = \begin{cases} \theta_1 - \theta_2, if -\pi < \theta_1 - \theta_2 \le \pi \\ 2\pi + \theta_1 - \theta_2, if\ \theta_1 - \theta_2 \le \pi \\ 2\pi - \theta_1 + \theta_2, if\ \theta_1 - \theta_2 > \pi \end{cases}$$

Now, the feature vector MFV_k^i of minutiae P_i from its k-nearest neighbours P_k is translational and rotational invariant. So it can directly be used for matching. Since, the local structure contains few nearest minutiae, however the errors could be introduced with the detection of false minutiae. To minimize the effect of false minutiae, a threshold (th) is considered. The similarity level (Sim_j^i) between feature vector of minutiae i of input fingerprint and feature vector of minutiae j from template can be calculated as:

$$Sim_j^i = \begin{cases} \dfrac{th - W\left|MFV_k^i - MFV_k^j\right|}{th}, if\ W\left|MFV_k^i - MFV_k^j\right| < th \\ 0, otherwise \end{cases}$$

Where th is the threshold which is 6xM, where M is the length of feature vector.$W$is the weight associated with each feature of the feature vector. $W$is defined as:

$$W = (w_D, w_\theta, w_\varphi)$$

$$w_D = 1, w_\theta = w_\varphi = 0.3 \times {}^{180}/_{\pi}$$

Similarity value Sim_j^i must lie between 0 and 1. Where $Sim_j^i = 0$ means totally mismatch and $Sim_j^i = 1$ means highly matched.

Although similarity score of a local structure is a good way to sort template fingerprints according to the input fingerprint. However, alone it could increase the false acceptance ratio due the following factors:

(i) Local structure of same minutiae could be different with the changes in neighborhood

(ii) Presence of false minutiae could decrease the similarity score of fingerprints of same person

(iii) Even the absence of a single minutiae could distort the local structure and so the similarity score

Therefore, making the decision based on local structure is not reliable. To improve the reliability of matching a global structure matching is considered. The global structure matching process should be followed by local structure matching in order to improve the matching accuracy and decrease the searching time.

Global structure matching

Once the local structure matching is performed then all template fingerprints correspond to input fingerprint are sorted in descending order according to the average similarity score. Average similarity score of an input fingerprint X and template fingerprint Y can be calculated as the mean score of all local structure similarity score. Best matched template fingerprint $F2$ is considered for global matching with the input fingerprint $F1$. Matching certainty level (MCL) of the local structure of input fingerprint $F1$ and template fingerprint $F2$ can be calculated as:

$$MCL(i,j) = \begin{cases} 0.5 + 0.5 \times Sim_j^i, if \left|MFV_{F1}^i - MFV_{F2}^j\right| < G_{th} \\ 0, otherwise \end{cases}$$

Where G_{th} is the global threshold or global tolerance factor and is considered as $(8, \pi/6, \pi/6)$. Like average similarity score of local structure, the average global matching certainty level between input fingerprint $F1$ and template fingerprint $F2$ can be calculated as:

$$GMS(F1, F2) = 100 \times \frac{\sum_{i,j} MCL(i,j)}{\max(N_{F1}, N_{F2})}$$

Where N_{F1}, N_{F2} are the total minutiae in input as well as in template fingerprint.

Experimental Results

The approach is tested on IIIT-D latent fingerprint dataset[7]. The dataset contains latent fingerprints of 15 subjects with all 10 fingerprints. All the fingerprints are unique in nature, therefore it has total 150 categories. The dataset is prepared in multiple sessions with two different backgrounds (i) tile and (ii) ceramic plate. Due to difference in timing in different session, the latent fingerprints contains different environmental factors such as moisture, wetness, and dryness. Canon EOS 500D with 15 Mega pixels resolution (4752 x 3168) camera is used to capture the lifted images. Corresponding to all 150 classes, there are total 1046 latent fingerprint and 150 plain fingerprints images in the dataset. All plain fingerprints are scanned at 1000 ppi. Some of the latent fingerprint images contain single impression of fingerprint, while some having multiple impressions as shown in

Some have partial impression while some have overlapped images. First the segmentation approach is applied to all latent fingerprints to segment single/multiple fingerprints from noisy background. Segmentation algorithms proposed in this paper segmented 2078 fingerprints from 1046 latent fingerprint images. We further divided the segmented latent fingerprints into two groups having (i) 1600 full impression and (ii) 478 partial impression. Images shown in Figure 2 are categorized into full impression fingerprints, while images and categorized into partial impression fingerprints.

Partial impression fingerprints are those having partial impression of the finger, relatively smaller friction ridge pattern area, and poor quality of ridge quality due to background noise.

Segmentation

For segmentation we developed 1000 positive and 1000 negative samples of size $w \times w$. The positive samples contain normal fingerprint as well as latent fingerprint images, while negative samples contain non-fingerprints. All the features are calculated for both the categories and performance of SVM classifier is tested for Radial Basis Function (RBF) as well as with Gaussian kernel. All the simulations are performed in MATLAB 2018a by varying the sample

Fig. 2 — Partial impression fingerprints

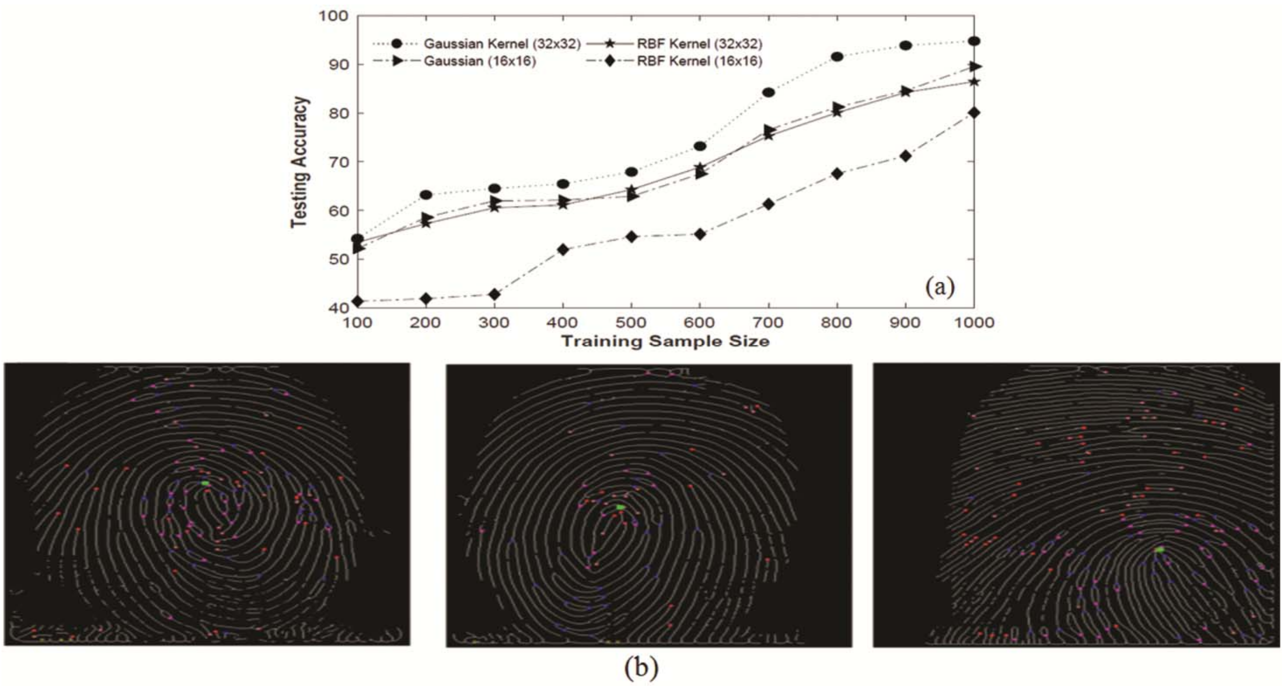

Fig. 3 — (a) Performance graph of SVM classifier on different training samples size and (b) Inverted skeleton image with core point (green), bifurcation (blue for $\theta \in [0^0, 180^0)$ and purple for $\theta \in [180^0, 360^0)$), delta points (gold), and ridge endings (orange for $\theta \in [0^0, 180^0)$ and red for $\theta \in [180^0, 360^0)$)

size from 100 to 1000. Figure 3(a) represents the performance graph of the segmentation approach by varying the training samples. It is observed from Figure 3(a) that classification accuracy is more with Gaussian kernel having 1000 training samples and 32x32 window size. Performance of the segmentation approach with 1000 samples is shown in Table 1.

Indexing

Against 2078 extracted latent fingerprints, we have only 150 plain fingerprints of 661x508 size. All the segmented latent fingerprints are searched against 150 plain fingerprints. For indexing, first we extracted the minutiae of all plain fingerprint images using the algorithm discussed and stored it in the database. Extracted minutiae of first three subjects are shown in Figure 3(b). As the images are of high quality, therefore average number of minutiae is 102. Minimum and maximum number of minutiae are 65 and 150. According to, if more than 12 minutiae are present and fingerprint is sharp then identity is

Table 1 — Segmentation accuracy of latent fingerprints using SVM with RBF and Gaussian kernel

Classifier	Kernel	Window Size ($w \times w$)	Accuracy
SVM	RBF	16x16	80.09%
SVM	RBF	32x32	86.44%
SVM	Gaussian	16x16	89.54%
SVM	Gaussian	32x32	94.77%

certain. Minutiae around borders/corners have minimum contribution in accuracy, therefore they have been removed. After removal average number of minutiae comes to 90 which is still in large number. In this experiment, we have decreased the minutiae and their corresponding average indexing time as well as accuracy has been obtained. The simulations are carried out in two ways: average accuracy and indexing time are calculated for (i) 1600 full impression images and (ii) 478 partial impression images. For indexing, first minutiae are extracted for segmented full and partial fingerprint images and then indexing algorithm is applied to evaluate the performance of the algorithm. Average indexing time and accuracy on laptop having Intel core i5 processor and 8 GB RAM corresponds to average number of minutiae are shown in Table 2 and Table 3. Since, we have only one plain sample of a person, therefore the accuracy is calculated on the basis of first indexed image. Average number of template's minutiae varies from 90 to 20 and the average indexing time and average accuracy are calculated for segmented 1600 full impression and 478 partial impression. For any query image, all the minutiae around the corners have been removed before processing. Partial fingerprints have significantly less number of minutiae as compared to full fingerprints. Average number of minutiae for 1600 full impression fingerprints is 76 while it is just 32 for 478 partial fingerprints. As observed from Table II and Table III that average indexing time as well as accuracy decreases with the decrement in average number of minutiae. Accuracy on full latent fingerprints are quite good, it is 95% when number of template's minutiae are 90. The accuracy is consistent even up to 40 numbers of minutiae. But, it degrades on further decrement in number of minutiae. The proposal approach also performed better with partial fingerprints. Accuracy in case of partial fingerprints is 71.97% when number of template's minutiae are 90 and 62.76% when minutiae is 40, however it decrease significantly as we further decrease the minutiae. Hence, limiting the number of extracted minutiae up to 40 is good according to the proposed approach.

Table 2 — CPU time in seconds with average number of minutiae

Number of Images	CPU time (secs) with average number of minutiae				
	90	60	40	30	20
1600 full impression fingerprints	9.73	7.12	5.30	3.46	2.17
478 partial impression fingerprints	7.19	5.15	3.52	2.77	1.09

Table 3 — Accuracy in (%) with average number of minutiae

Number of Images	Accuracy (in %) with average number of minutiae				
	90	60	40	30	20
1600 full impression fingerprints	95.00	93.75	91.00	80.06	68.13
478 partial impression fingerprints	71.97	65.69	62.76	46.65	34.52

Conclusion

This study described a fast latent fingerprint indexing approach with the help of minutiae based rotational and translational features and a global matching approach. Generally, local minutiae structures in query fingerprint lead to high similarity score with non-mated templated fingerprints. Therefore, global matching in combination with local matching boost the indexing efficiency. Usually, latent fingerprints are lifted from the objects or crime scenes, therefore it possess many challenges such partial impression of the finger, background noise, poor ridge clarity, and large non-linear distortions, which leads to poor identification. In order to increase the matching accuracy a novel machine learning based segmentation algorithm is also developed as a pre-processing step. Finally, the experiments illustrate that the proposed approach is outstanding for latent fingerprint indexing.

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