Fingerprint Indexing using Minutiae and Pore Features

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Abstract—*In this paper, we propose level-2 and level-3 feature based fingerprint indexing algorithm to improve the speed and accuracy of identification. Indexing parameters are computed using the minutiae and pore features. The identification performance is further improved by incorporating Dempster Shafer theory based match score fusion algorithm. Experimental results on a high resolution fingerprint database show that the proposed algorithm improves the identification performance by at least 10% compared to existing fingerprint identification algorithms.*

Keywords: Fingerprint Indexing, Identification, Dempster Shafer Theory, Fusion

1. Introduction

Fingerprint recognition is a well studied research area in which significant results have been achieved. Fingerprint recognition can be divided into two tasks: verification and identification. Fingerprint verification is used to verify the identity of an individual by 1:1 matching whereas identification is used to establish the identity by 1:N matching. Fingerprint identification thus becomes more challenging than verification because of high system penetration and false acceptance rate. In literature, there are three methods to perform identification [1]:

- Brute force: Matching probe image to all gallery images.
- Classification: Matching probe image to gallery images with corresponding class (left loop, right loop, whorl, arch, and tented arch).
- Indexing: Matching indexing parameters of probe image with gallery images to enable sublinear time lookup.

Brute force identification and classification methods have certain limitations. For example, in applications such as law enforcement and border security where database contains millions of images, the first method would require significantly large number of comparisons and is not feasible. Classification method divides the database into different classes depending on level-1 features or some other classification technique. This method reduces the number of images to a certain extent but since the number of features for classification is small, each class still contains large number of images. In both cases, large number of gallery images lead to high system penetration coefficient and false accept rate.

To address the challenges of these two methods, researchers have proposed indexing based identification algorithms. Database indexing fastens the identification process by reducing the number of required matches without compromising the verification performance. Germain *et al.* proposed a flash algorithm for fingerprint indexing [2]. Bebis *et al.* proposed the Delaunay triangulation of minutia points to perform fingerprint indexing [3]. Boer *et al.* used the registered directional field estimate, FingerCode and minutiae triplet along with their combination to index fingerprint databases [4]. Bhanu and Tan [5] generated minutiae triplets and used angles, handedness, type, direction, and maximum side as the features for indexing. They also applied some constraints on minutiae selection to avoid spurious minutiae. Further, Li *et al.* [6], Feng and Cai [7], and Choi *et al.* [8] proposed indexing algorithms using different level-2 fingerprint features [1]. Existing algorithms have only used level-2 features for indexing. While level-3 features provide discriminating information compared to level-1 and level-2 features [9][1], researchers have not yet explored level-3 features for fingerprint identification.

In this paper, we propose the use of level-2 minutiae and level-3 pore features based indexing algorithm for fingerprint identification. Minutiae and pore based indexing parameters are computed for minutiae triplets and top matches from gallery images are obtained. We further extend the proposed identification algorithm by using Dempster Shafer theory [10], [11] to fuse the match scores. Section 2 presents the proposed indexing algorithm and Section 3 presents the proposed Dempster Shafer theory based match score fusion algorithm. Experimental results are described in Section 4.

2. Proposed Fingerprint Indexing Algorithm

In the proposed fingerprint indexing algorithm, level-2 minutiae features and level-3 pore features form the indexing parameters. Minutiae are computed using the minutiae extraction algorithm described in [12] and pore features are computed around each minutiae by using the pore extraction algorithm described in [13]. The first step in the proposed algorithm is to form a Delaunay triangle using minutia information as follows:

[1]Fingerprint features are divided into three levels: level-1 features (example: whorl and arch), level-2 features (example: ridge ending and bifurcation), and level-3 features (example: pores and ridges).

1) Given n minutiae points computed using the minutiae extraction algorithm [12], first compute the Voronoi diagram which decomposes the minutiae points into regions.
2) Use Voronoi diagram to compute the Delaunay triangulation by joining the minutiae coordinates present in the neighborhood Voronoi regions. Fig. 1 shows an example of Voronoi diagram and Delaunay triangulation of fingerprint minutiae.

Each triangle in Delaunay triangulation is then used as minutiae triplets [5]. Tuceryan and Chorzempa [14] found that Delaunay triangulation have the best structural stability and hence minutiae triplets computed from Delaunay triangulation are able to sustain the variations due to fingerprint deformation [3]. Further, as shown by Bebis *et al.* [3], any local variation due to noise or inserting new feature point affects the Delaunay triangulation only locally.

From the minutiae triplets generated using the Delaunay triangulation, we compute the indexing parameters which include both minutiae and pore information. Indexing parameters are then computed as follows:

1) **Average angle in minutiae triplet (α_{avg}):** Let α_{min} and α_{max} be the minimum and maximum angles in a minutiae triplet. Average angle of the minutiae triplet is defined as, $\alpha_{avg} = (\alpha_{min} + \alpha_{max})/3$. Average angle vector is then computed for all the minutiae triplets in a given fingerprint.
2) **Triangle orientation (O):** According to Bhanu and Tan [5], triangle orientation is defined as $\phi = sign(z_{21} \times z_{32})$, where $z_{21} = z_2 - z_1$, $z_{32} = z_3 - z_2$, $z_{13} = z_1 - z_3$, and $z_i = x_i - jy_i$. z_i is computed from the coordinates (x_i, y_i), $i = 1, 2, 3$ in minutiae triplet. Triangle orientation vector, O, is then computed for all minutiae triplet in a given fingerprint.
3) **Triplet density (D):** Minutiae density is defined in a local region, i.e., if there exists n' minutiae in a local region centered at a minutiae then minutiae density is n'. For a minutia triplet, we define triplet density as the average minutiae density of three minutia that form the triplet. If n'_1, n'_2, and n'_3 are the minutiae density of three minutiae, then triplet density is $(n'_1 + n'_2 + n'_3)/3$. Similarly, triplet density is computed for all the triplets in the fingerprint image and triplet density vector D is formed.
4) **Longest edge in minutiae triplet (E):** Longest edge in each minutiae triplet is used to form the longest edge vector, E.
5) **Min-Max distance between minutiae points and k-nearest neighbor pores (M_p):** For every minutiae point, compute the distances between minutiae and k-nearest neighboring pores which are on the same ridge. Out of k distances, use the minimum and maximum distances as indexing parameters. Min-Max distance, vector (M_p), is then generated from all the minutiae in a fingerprint image.
6) **Average distance of k-nearest neighbor pores (P_{avg}):** Average distance vector of k-nearest neighbors pores, P_{avg}, is formed by computing the average distance of k-nearest neighbor pores of all the minutia.

These indexing parameters $I(\alpha_{avg}, O, D, E, M_p, P_{avg})$ are further used for fingerprint indexing and identification.

2.1 Matching Indexing Parameters

For matching two fingerprint indexing parameters, $I^1(\alpha^1_{avg}, O^1, D^1, E^1, M^1_p, P^1_{avg})$ and $I^2(\alpha^2_{avg}, O^2, D^2, E^2, M^2_p, P^2_{avg})$, we apply a thresholding scheme. First, corresponding Delaunay triangles and their respective indexing parameters are matched by applying the following conditions:

- Two average angle vectors are said to be matched if $|\alpha^1_{avg} - \alpha^2_{avg}| \leq t_{avg}$.
- Two orientation vectors are said to be matched if $O^1 = O^2$.
- Two triplet density vectors are considered to be matched if $|D^1 - D^2| \leq t_D$.
- Two largest edge vectors are said to be matched if $|E^1 - E^2| \leq t_E$.
- Two Min-Max vectors are said to be matched if $|M^1_p - M^2_p| \leq t_{M_p}$.
- Matching criterion for two average diameter vectors is $|P^1_{avg} - P^2_{avg}| \leq t_{P_{avg}}$.

Here, $t_{avg}, t_D, t_E, t_{M_p}, t_{P_{avg}}$ are the thresholds empirically computed using the gallery fingerprint images. These thresholds are geometric constraints to reduce the number of false cases. Indexing score, s is finally computed as follows:

$$s = \frac{1}{n} \sum_{i=1}^{n} T_i \quad (1)$$

where T_i be the number of matched Delaunay triangles in two fingerprint images where $i = 1, ..., n$ and n is the number of corresponding minutiae triplets. In a similar manner, we extend the proposed indexing algorithm for fingerprint identification by matching indexing parameters of probe fingerprint image with the gallery fingerprint images. Let j be the number of gallery fingerprint images and s_j be the indexing scores for j comparisons. The indexing scores, s_j are sorted and top M matches are selected as possible matches, where M is significantly smaller than the total number of gallery images, j.

3. Match Score Fusion for Improved Performance

For every probe image, the proposed indexing algorithm yields top M matches from gallery database. To further improve the identification accuracy, we apply match score fusion using level-2 feature and level-3 pore feature based

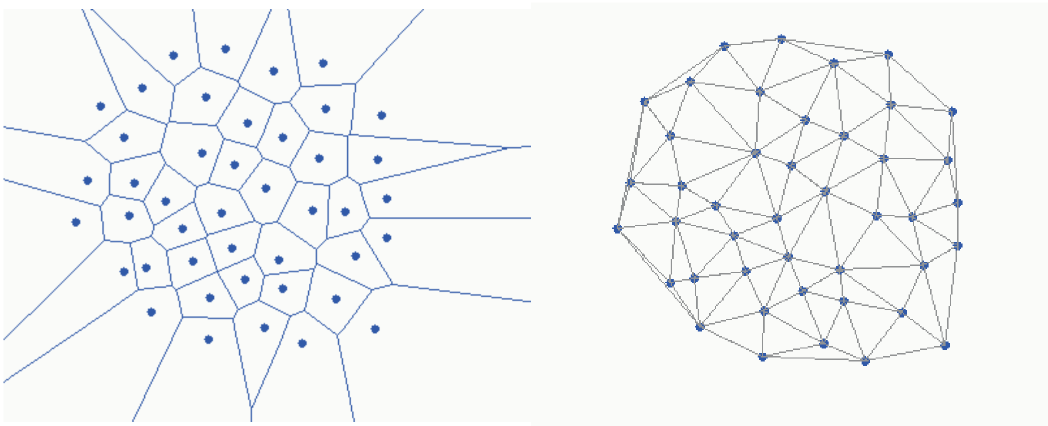

Fig. 1: Example of Voronoi diagram and Delaunay triangulation of fingerprint minutia.

recognition algorithm. Since $M << j$, (for instance, M = 50 and j = 1000), we can perform multimodal match score fusion for all M matches without considerably increasing the time complexity and enhancing the identification performance. We propose the Dempster Shafer theory [10], [11], [15] based match score fusion algorithm for fingerprint identification.

Let Θ be a finite set of mutually exclusive and exhaustive proposition or commonly known as frame of discernment. The power set 2^{Θ} is the set of all subsets of Θ including itself and null set $\emptyset$. Each subset in the power set is called focal element. A value between [0, 1] is assigned to each focal element which is based on the evidence. 0 shows no belief and 1 shows total belief. Basic belief assignment (bba), in DS theory, is assigned to the individual proposition which is also known as mass of the individual proposition. It is assigned to every subset of the power set. If bba of an individual proposition A is $m(A)$ then,

$$\sum_{A \subset \Theta} m(A) = 1 \tag{2}$$

Also, bba of a null set is zero, i.e.

$$m(\emptyset) = 0 \tag{3}$$

Further, multiple evidences can be combined using the Dempster's rule of combination. Let A and B be used for computing new belief function for the focal element C. Dempster's rule of combination is written as,

$$m(C) = \frac{\sum_{A \cap B = C} m(A)m(B)}{1 - \sum_{A \cap B = \emptyset} m(A)m(B)} \tag{4}$$

In the proposed match score fusion algorithm, there are three elements:

- Prior probability of correct verification of minutiae and pore feature based verification algorithms. Let verification accuracies of minutiae and pore based recognition algorithms be ν_m% and ν_p%. Prior probabilities of minutiae and pore based algorithms, π_m and π_p, are computed as follows.

$$\pi_m = \frac{\nu_m}{\nu_m + \nu_p} \; , \quad \pi_p = \frac{\nu_p}{\nu_m + \nu_p} \tag{5}$$

- Rank prior of M indexed gallery images. Let the rank of indexed gallery fingerprint be M', where $M' \leq M$. The rank prior can be computed as,

$$r = \left(\frac{M - M' + 1}{M} \right) \tag{6}$$

- Normalized match scores MS_m and MS_p, $[0 \leq (MS_m, MS_p) \leq 1]$ obtained by matching minutiae and pores computed from two fingerprint images are used as the third parameter in the proposed fusion algorithm.

In the propose fusion algorithm, the frame of discernment Θ is $\{\theta_{genuine}, \theta_{impostor}\}$ and power set is $\{\theta_{genuine}, \theta_{impostor}, \theta_{genuine} \cup \theta_{impostor}\}$. Basic belief assignment for both minutiae and pore based algorithm is computed using Equations 7 - 11.

$$m_m(\theta_{genuine}) = \frac{r \pi_m MS_m}{\pi_m MS_m + \pi_p MS_p} \tag{7}$$

$$m_m(\theta_{impostor}) = 1 - m_m(\theta_{genuine}) - \epsilon_0 \tag{8}$$

$$m_p(\theta_{genuine}) = \frac{r \pi_p MS_p}{\pi_m MS_m + \pi_p MS_p} \tag{9}$$

$$m_p(\theta_{impostor}) = 1 - m_p(\theta_{genuine}) - \epsilon_0 \tag{10}$$

$$m_m(\theta_{genuine} \cup \theta_{impostor}) = m_p(\theta_{genuine} \cup \theta_{impostor}) = \epsilon_0 \quad (11)$$

where, $\epsilon = 0.05$ is a small error parameter introduced to handle errors during the indexing process.

Belief assignments of minutiae and pores based algorithm are then fused using Equation 12.

$$m_{fused} = m_m \oplus m_p \quad (12)$$

where $\oplus$ denotes the Dempster rule of combination defined in Equation 3. Using the proposed fusion algorithm, we match the probe fingerprint and top M matches obtained from the proposed indexing algorithm and compute m_{fused}. Finally, resorting of M matches is performed based on m_{fused} values and the new ranking is used for identification.

4. Experimental Results

The proposed multimodal fingerprint identification algorithm is validated on a database which contains high resolution fingerprint images from 500 different classes. Fingerprint images are scanned at 1000 ppi to facilitate the extraction of both minutiae and pores details. Further, there are 10 images per class out of which three fingerprint images per class are used as gallery images and rest of seven fingerprint images per class are used as probe images. Minutiae extraction and matching algorithm described in [12] are used in the indexing algorithm and for generating the match scores, MS_m. Match scores for pore features, MS_p, are computed using the algorithm described by Kryszczok *et al.* [13]. Match scores of both minutiae and pore based algorithms are normalized in the range of [0, 1], where 0 represents 'perfect reject' and 1 represents 'perfect accept'.

We first use gallery images to compute the thresholds used in the indexing algorithm, which are found to be $t_{avg} = 6^0$, $t_D = 2$, $t_E = 12$, $t_{M_p} = 2$, and $t_{p_{avg}} = 1$. We further observed that the value of k in computing the Min-Max distance vector (M_p) and average distance vector (P_{avg}) should be 3 because in several cases, number of minutiae under consideration has only three pores. Using these parameters, we then compute the performance of the proposed indexing algorithm and DST based match score fusion algorithm. Experimental results are divided into two parts: evaluation of the proposed indexing algorithm and evaluation of the proposed match score fusion algorithm.

4.1 Evaluation of Proposed Indexing Algorithm

Using gallery and probe fingerprint images, we first evaluate the performance of the proposed indexing algorithm. We compute the rank based identification accuracy of the indexing algorithm and compare the performance with other existing fingerprint indexing algorithms described in [3] and [5]. Fig. 2(a) shows that rank 1 identification rate (M = 1) of the proposed algorithm is 79.1% whereas other two algorithms yield 70.4% and 71.7%. For rank 5 identification (M = 5), the proposed indexing algorithm outperforms other two algorithms by 15-18% and yields an accuracy of 89.5%. For rank 50 (M = 50), identification accuracy of the proposed algorithm improves to 96.8% whereas existing indexing algorithms yield the identification accuracy of 88.8% and 89.9% respectively. Since the proposed algorithm uses both level-2 and level-3 features extracted from fingerprint images, the performance is relatively higher than existing algorithms.

We further evaluate the performance of the proposed indexing algorithm with varying database sizes. We first computed the rank 1 identification accuracies of the proposed and existing indexing algorithm with 100 classes. We then increase the number of classes by a factor of 100 and compute the identification accuracies. Fig. 2 shows that with increasing database size, the proposed algorithm yields better performance compared to other existing indexing algorithms.

4.2 Evaluation of Proposed Match Score Fusion Algorithms for Identification

In this section, we evaluate the performance of the proposed Dempster Shafer theory based match score fusion algorithm for identification. For this experiment, we choose M as top 50 matches obtained from the previous experiment. We apply the proposed match score fusion algorithm and resort the ranking based on the fused information. Fig. 3 shows that the identification performance improves considerably by applying the proposed match score fusion algorithm. For example, after applying the fusion algorithm, identification accuracy at rank 5 is 90.6% which is an improvement of 1.1%. Further, 98.8% identification accuracy is obtained for top 50 matches when the proposed match score fusion algorithm is used in conjunction with the proposed indexing algorithm. These experiments thus show that the proposed algorithms provide better performance compared to existing algorithms. We also computed the average time required for identifying a probe fingerprint with and without the proposed indexing and match score fusion algorithm. Using the brute force method for identification, identifying one probe image requires an average of 316 seconds, whereas with the proposed fusion algorithm, the average identification time reduces to 82 seconds.

5. Conclusion

Existing fingerprint identification algorithms use level-2 features for matching. However, forensic scientists have suggested that level-3 features are more discriminating compared to level-2 features. In this paper, we proposed the use of level-2 and level-3 features for fingerprint identification using indexing techniques. We further extended the identification algorithm by incorporating Dempster Shafer theory based match score fusion algorithm. Experimental results on a high resolution fingerprint database show that the

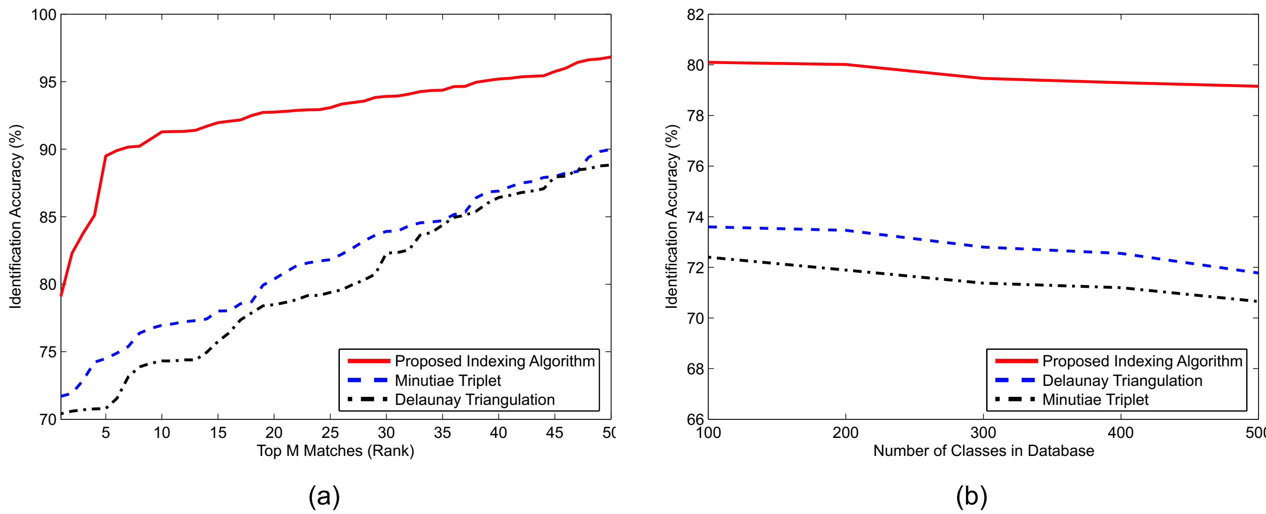

Fig. 2: (a) CMC plot of the proposed indexing algorithm. Performance is compared with Delaunay triangulation [3] and minutiae triplet [5] based existing indexing algorithms. (b) Effect of size of database on indexing algorithms.

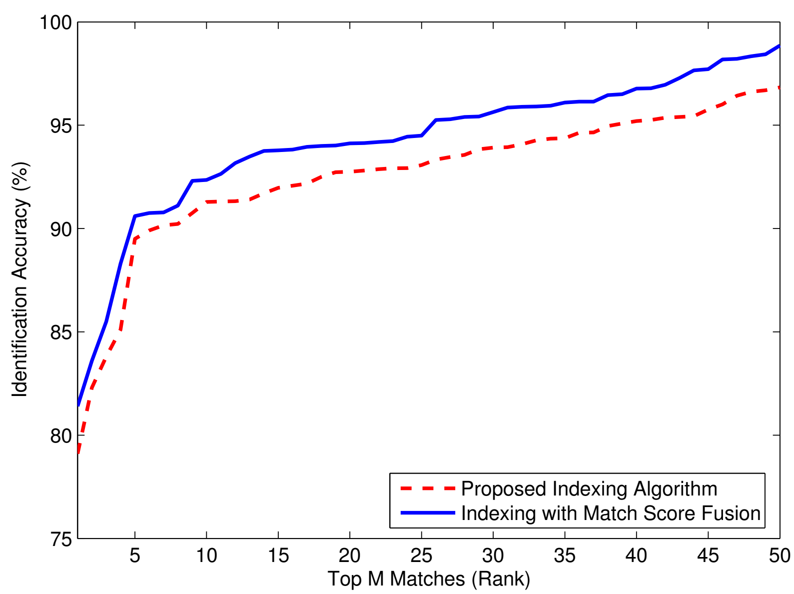

Fig. 3: CMC plot demonstrating the performance of the proposed indexing algorithm with and without the proposed match score fusion algorithm.

proposed algorithm improves the speed and yields the rank 1 identification accuracy of 81.4% which is at least 10% better than existing indexing based fingerprint identification algorithms.

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