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Nearest Neighbor Minutia Quadruplets based Fingerprint Matching with Reduced Time and Space Complexity

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***Abstract*—The fingerprint biometric is often used as the primary source of person authentication in a large population person identity system because fingerprints have unique properties like distinctiveness and persistence. However, the large volumes of fingerprint data may lead to the scalability issues which are to be addressed in the context of memory and computational complexity. In this paper, an attempt is made to develop an efficient fingerprint matching algorithm using nearest neighbor minutia quadruplets (NNMQ). These minutia quadruplets are both rotation and translation invariant. Experimental results demonstrate that the proposed fingerprint matching algorithm achieves the reduced space and time complexities with the publicly available standard fingerprint benchmark databases FVC ongoing, FVC2000 and FVC2004.**

Keywords*—Fingerprint recognition, k-nearest neighbors, minutia quadruplets.

I. INTRODUCTION

A fingerprint[1] is the more accurate biometric which consists of ridges and furrows on its surface. The uniqueness of a fingerprint biometric can be determined by the minutia details, called minutia points. These points can be identified by the local ridge features, namely, a ridge bifurcation and a ridge ending. The majority of the fingerprint matching algorithms are developed using mintutia points [2], [3], [4]. Some of the fingerprint matching algorithms have been proposed using the local minutiae descriptors [5], [2], [6], [7]. Few fingerprint matching techniques combine ridge flow orientation with minutiae matching information either at scores by combining scores from global orientation field matching and minutiae matching [8], [9] or at feature level by including ridge flow features in local minutiae descriptors [10], [8].

There are three different approaches in fingerprint matching, namely, minutiae-based [11], ridge feature-based [12] and correlation-based [1]. Minutiae-based fingerprint matching methods finds number of minutiae matches between an input fingerprint (probe) and an enrolled fingerprint (gallery). This is the most popular and widely used approach. In the correlation-based fingerprint matching two fingerprint images are overlapped and the similarity between corresponding pixels is determined for the different alignments. this kind of matching technique is computationally expensive and prone to distortions in the images. In ridge feature-based fingerprint matching features of the fingerprint ridge pattern like local ridge orientation, frequency and shape are extracted for comparison. These features may be more reliable for comparison in fingerprints of low-quality images than minutiae features. The matching of the fingerprint matching algorithm is correct when there are genuine matches (true accepts) and genuine rejects (true non-matches). The matching is wrong when there are impostor matches (false accepts) and impostor non matches (false rejects). The performance of fingerprint recognition is not 100% efficient. The important issue is to limit the errors FAR (False Accept Rate) and FRR (False Reject Rate) as much as possible.

Earlier the fingerprints were widely used for criminal investigation systems, but now the fingerprint recognition systems play a key role in civilian applications in order to provide public services and welfare schemes for the benefit of the people in the society. The large-population person identity programs (for example India's Aadhaar and UAE's border security programs) choose the fingerprint biometrics as the one of the source of person authentication. The fingerprint matching algorithm is the key component in fingerprint recognition systems. In the context of large scale fingerprint recognition systems, the fingerprint matching system should utilize the minimum computational complexity and memory space, otherwise the system faces scalability issues.

In this paper, a hybrid fingerprint matching algorithm is proposed based on k-nearest neighbor and minutia quadruplets. The rest of the paper is organized as follows: In section II, the existing fingerprint matching techniques are presented. The proposed fingerprint matching algorithm is presented using the representations of quadruplets in section III. Experimental results for the proposed algorithm are discussed in section IV. Key conclusions are discussed in section V.

II. EXISTING FINGERPRINT MINUTIA MATCHING METHODS

There are mainly two types of minutia matching involved with Minutiae-based matching one is with local minutiae and another one with global.In global minutiae matching, highly discriminative features of the fingerprint are used for comparison. The least distance between minutiae in the probe and enrolled fingerprint is determined, whereas in local minutiae matching, structures are defined based on some geometric or feature based technique which can be used in comparing

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fingerprint images for matches or non-matches. Global matching is accurate but has high computational complexity, low distortion tolerance, heavy template size and slow speed of computation.

A. Feature Extraction

Minutiae features were extracted from the fingerprint images using a NIST MNTDTCT algorithm. The fingerprint images were unprocessed and hence noisy. This led to the extraction of spurious minutiae as well. The x, y (coordinate locations), direction, quality of the bifurcation and ridge-end minutiae were extracted. The extracted features for every single image were stored in a ISO 19794-2 format.

III. Proposed Fingerprint Matching Algorithm using Quadruplets

In this section, the proposed fingerprint matching algorithm is explained. The quadruplet details are given first and then explained the k-nearest neighbor matching and global minutia matching using quadruplets.

A. Quadruplets

Let A be the set of fingerprint minutiae and the n-quadruplets can computed as follows. The k-nearest neighbors from the set A are computed for all $m \in A$ in order to find all n-quadruplets which have m and three of its nearest minutiae which is tolerant to the low quality. The following figure illustrates the sample quadruplet representation of minutia points.

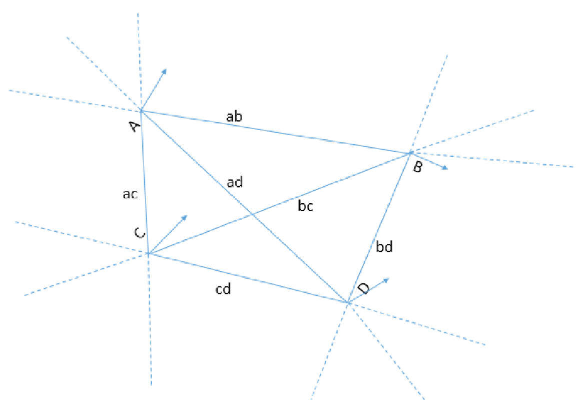

Fig. 1. Quadruplet representation of minutiae

The euclidean distances between each pair of minutia are represented in Fig. 1 as ab, bc, cd, da, ad and bc. Each minutia point will be having 5 characteristics x, y, $Direction$, $Type$ and $Quality$. We considered x, y and $Direction$ for matching.

In Fig. 2, illustrates each minutiae pair features for matching ab is the euclidean distance , α is direction at minutiae A, β is direction at B.

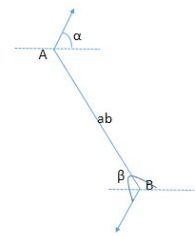

Fig. 2. characteristics of minutiae pair

B. k-nearest neighbor matching algorithm

This step finds the similar mates from query template and probe template using k-nearest neighbor local minutia matching techniques. If P and Q are probe and reference minutia set: $P_{1..m} = \{Dist_p, Dir_p\}$, $Q_{1..n} = \{Dist_q, Dir_q\}$.

- Query and reference ISO templates as input.
- Get the query and reference templates X, Y, direction, type and quality.
- Compute the edge pair information for each minutia to all other minutia.
- Sort the edge pair information using euclidean distance.
- Find the mates for each minutia in query and probe template using k-nearest neighbors (k= 7,8,9 and 10), using Euclidean distance and direction difference.
- Let P and Q be the fingerprint minutia of probe and gallery images, respectively, and R and S be the minutia edge pair information. Let M be the set of local minutia pairs which are matched from query and probe template.
- Sort minutia pair information in query and probe in ascending order using Euclidean distance.
- Find the similarity from R to S using nearest k-neighbors (6,7,8 and 9) with distance and direction parameters.

C. Global Minutiae Matching using Minutia Quadruplets

This step uses each minutiae pair as reference pair for quadruplet calculation, now we will form the quadruplets using each minutia to all other minutia. If some quadruplet is formed then the score will be increased. The following three conditions should be considered to determine whether the two minutia at global level are matched in order to overcome the tolerance to distortions.

- the Euclidean distance between two minutiae $<$ threshold $DistThr$.
- the difference between minutia directions $<$ direction threshold $DirDiff$.
- the directions differences relative to reference minutiae pair $<$ threshold $SlpDiff$.

IV. Experimental Results

The experiments are conducted on the standard fingerprint benchmark data, FVC ongoing competition. Table I shows that the proposed fingerprint matching algorithm outperforms in the complexity point of view, when compared to the other algorithms (MintModel, MAJU-VISPRS-FIS-algo, ABVD and (BaseLine)) which were published from academic institutions.

TABLE I. Time and space complexity results on FVC ongoing data

Algorithm	Space (KB)	Time (ms)
MntModel	2044	116
MAJU-VISPRS-FIS-algo	8672	21
ABVD	11704	74
MCC(BaseLine)	24076	242
FMIsoMatcher (proposed)	1992	19

Accuracy indicators of the proposed algorithm published on FVC ongoing data is given in Table II.

The graphs FMR vs. FNMR, Score distributions and DET on FVC ongoing data are illustrated in Figs. 3(a), 3(b) and 3(c), respectively.

Fig. 4. Non-matched pair from FVC DB

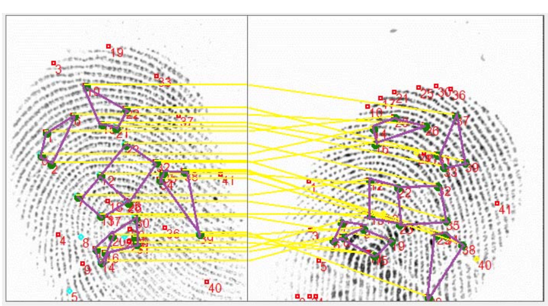

Fig. 5. Matched pair from FVC DB

The failure in the above pair is mainly due to less common area form probe finger image to gallery finger image, resulted in very few common minutiae. The success fair even though the captured finger is small, the common area from probe finger image to gallery image is good enough to match, resulted in very good score.

The experiments are conducted on FVC 2004 fingerprint database. The results are compared with M3GL Triples algorithms as shown in Table III *(* indicates: local nearest neighbors=8, distance threshold=12, global distance threshold =12 and angle threshold = 30) (** indicates: local nearest neighbors=12, distance threshold=10, global distance threshold =12 and angle threshold = 30)*. The ROC curve for the same experiments are illustrated in Figs. 6, 7 and 8. The proposed fingerprint algorithm is evaluated for two different settings of parameters. One is having local nearest neighbors=8, distance threshold=12, global distance threshold =12 and angle threshold = 30. The other parameter are local nearest neighbors=12, distance threshold=10, global distance threshold =12 and angle threshold = 30.

TABLE III. Equal error rates for the fingerprint matching using triplets and quadruplets on FVC 2004 database

Database	EER (triplets)	EER (quadruplets) *	EER (quadruplets) **
DB1A	22.9	10.05	7.53
DB2A	20.7	10.93	7.87
DB3A	8.9	8.50	6.50
DB4A	24.2	7.79	6.05

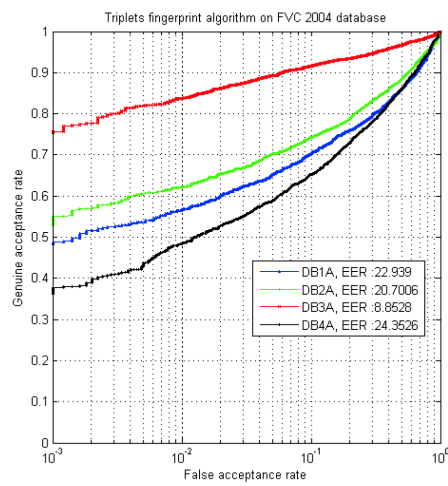

Fig. 6. ROC curve for the fingerprint matching using triplets on FVC 2004 database

V. Conclusion

The existing algorithms have few limitations which allows the utilization of much space for storing fingerprint data. In this paper, the proposed fingerprint matching algorithm used the new representation of minutia points using quadruplets. The experiments have proved that the algorithm achieves the the requirement of minimum space and time complexity without compromising the accuracy.

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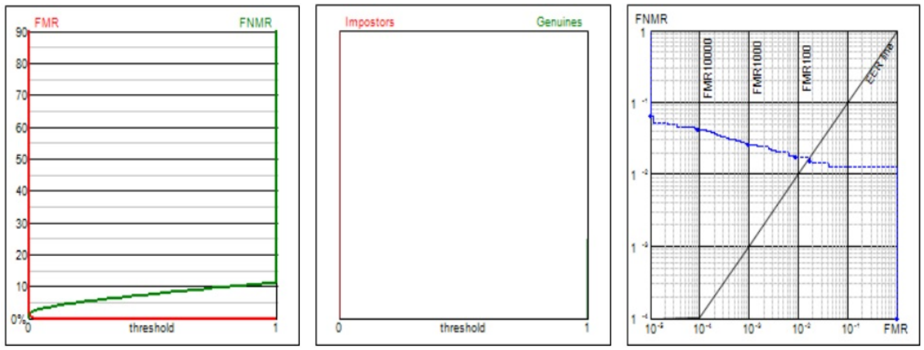
TABLE II. ACCURACY INDICATORS OF THE PROPOSED ALGORITHM FVC ONGOING DATA

EER	FMR_{100}	FMR_{1000}	FMR_{10000}	$Zero_{FMR}$	$Zero_{FNMR}$
1.322% (0.901% - 1.742%)	1.742%	2.615%	4.242%	6.573%	100%



(a) (b) (c)

Fig. 3. Results on FVC Ongoing: (a) FMR(t) and FNMR(t) graphs (b) Score distributions (c) DET graph

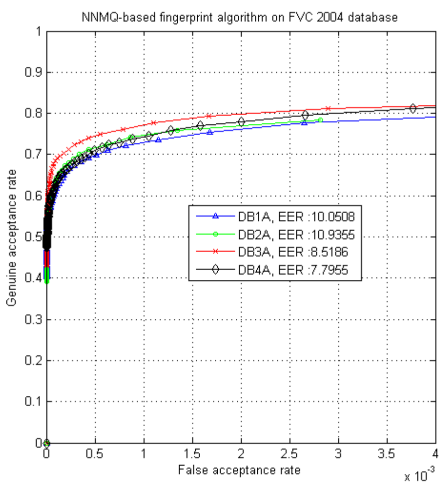


Fig. 7. ROC curve for the fingerprint matching using quadruplets on FVC 2004 database (* indicates: local nearest neighbors=8, distance threshold=12, global distance threshold =12 and angle threshold = 30)

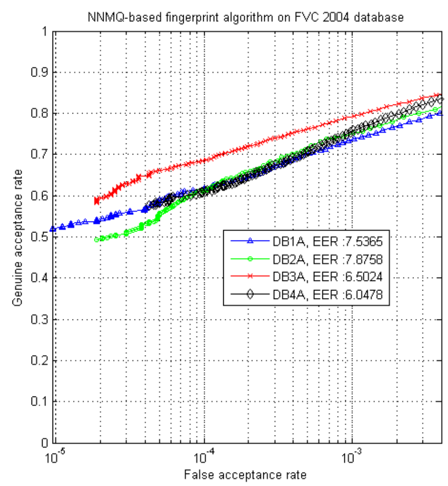


Fig. 8. ROC curve for the fingerprint matching using quadruplets on FVC 2004 database (* indicates: local nearest neighbors=12, distance threshold=10, global distance threshold =12 and angle threshold = 30)

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