Algorithm for retrieving candidate images

Let $S(x) = \{a_1, a_2, \ldots, a_k\}$ be the index string of the probe p, Q be the number of quadruplets in the probe and $\mathbf{T}_{G \cdot k}$ be the table storing the accumulators for the images in the gallery.

1. Sort $S(p)$ in descending order resulting in a sorted list $\{a_{i1}, a_{i2}, \ldots, a_{ik}\}$.
2. Find the top r clusters of the probe that contain at least 60% of the quadruplets.
3. For each gallery image g sum the accumulators in $\mathbf{T}$ corresponding to the r clusters. Let the sum be C^g.
4. Sort C^g for $g = 1 \ldots G$ in descending order.
5. Retrieve the gallery images corresponding to the top n C^g values.

Step 2 in the retrieval algorithm greatly reduces the number of clusters considered during retrieval, i.e., $r \leq 7$ for most cases. Furthermore, not every identity is assigned to every cluster and, therefore, many of the C^g sums will be equal to zero. An efficient implementation of Step 4 should discard all identities for which $C^g = 0$, prior to sorting.

4. Experiments

4.1. Experimental Setup

The databases used for the experiment were the Fingerprint Verification Databases (FVC) 2000, 2002 and 2004 [11, 12, 13] each of which has four datasets - DB1A, DB2A, DB3A and DB4A. Each dataset contains 8 images for each of 100 subjects making a total of 800 images.

The dataset used to create the index space was different from the dataset used for evaluating the proposed scheme. Images of the first 25 subjects in a dataset were used for creating the index space. For each indexing experiment, the dataset used for creating the index space was chosen based on the following criteria: the image resolution was the same as the dataset used for evaluation and the scanners had similar properties. Five different index spaces were created for the 12 databases used in the indexing experiments, as shown in Table 1.

For each subject, 4 impressions were placed in the gallery while the remaining 4 impressions were used as probes. The 4 gallery impressions for a subject were selected at random. The VeriFinger SDK was used to extract minutiae points from the images.

For images containing a large number of minutiae points, the number of quadruplets may be prohibitively large. Therefore, the number of quadruplets for each image used in the experiments was empirically limited to 1200 by removing the largest quadruplets. This was done by removing the quadruplets having a diagonal larger than a threshold until the number of the remaining quadruplets reached 1200. Furthermore, concave quadruplets were not used and all reflex quadruplets were converted to convex. Reducing the number of the quadruplets is performed offline for the images in the gallery.

The number of clusters, k, used in the experiments was 50 for each dataset. This number was chosen empirically as a compromise between high penetration rates (for k~30) and low hit rates for (k~100).

4.2. Evaluation of Indexing Performance

Indexing performance can be measured using two factors: the hit rate and the penetration rate. The hit rate denotes the fraction of probes for which the selected candidate list contains the correct identity, and the penetration rate denotes the average length of the candidate list retrieved for each probe.

5. Results

The results of the experiments on the 12 databases are reported in Figures 6, 7 and 8. For each experiment, the following three scenarios were considered: datasets in their original form; datasets with 20% spurious minutiae; and datasets with 20% missing minutiae. In each plot, the labels ending with N, M and S, represent the original, the missing and the spurious minutiae sets, respectively.

An important result of the proposed approach is the consistently low penetration rate at a hit rate of 100% which varies from 18.25% to 35.25% in the original minutiae sets, from 24.50% to 39.00% in the 20% missing minutiae sets, and from 34.75% to 57.5% for the 20% spurious minutiae sets.

Furthermore, deleting 20% of the minutiae points did not degrade the performance substantially. This shows that the minutiae quadruplets are robust to low quality images.

The results of the experiments with spurious minutiae are acceptable despite the generous quantity of randomly generated spurious data that were added to all the fingerprints. This shows that the minutiae quadruplet features are robust to a certain degree of noise in the fingerprints.

Finally, the results are similar across all databases showing the robustness of the proposed technique to different scanners.

An experiment in which the global feature, η, alone was used for indexing, led to penetration rates of 12.25% and 38% at 80% and 100% hit rates, respectively, on FVC 2000 DB1.

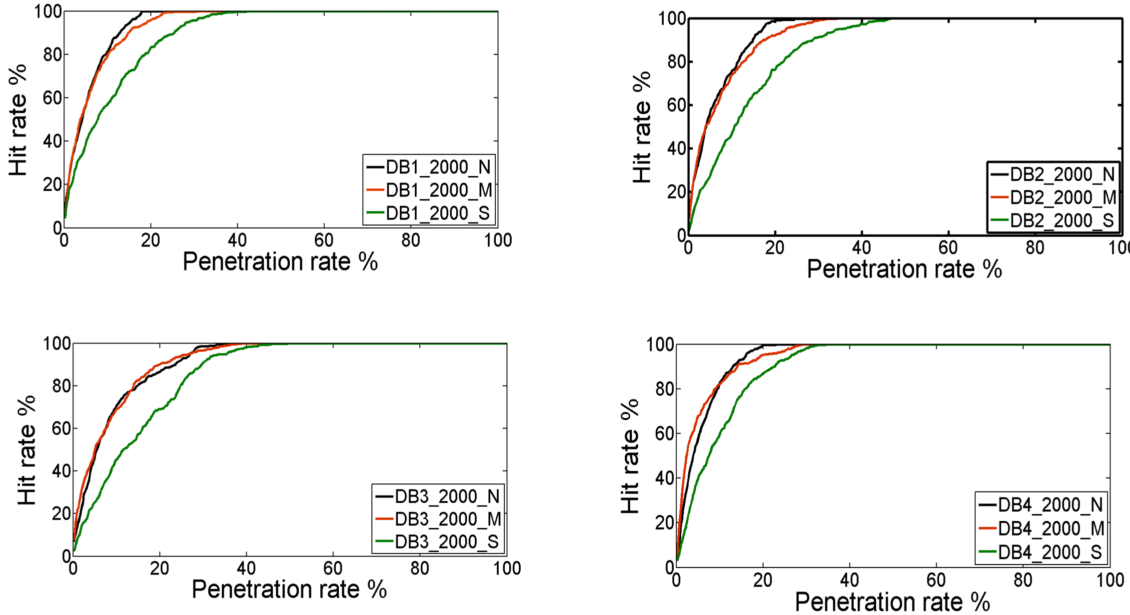

Figure 6: Performance on FVC 2000 DB1, DB2, DB3 and DB4 databases using the original minutiae data (N), 20% missing minutiae (M) and 20% spurious minutiae (S).

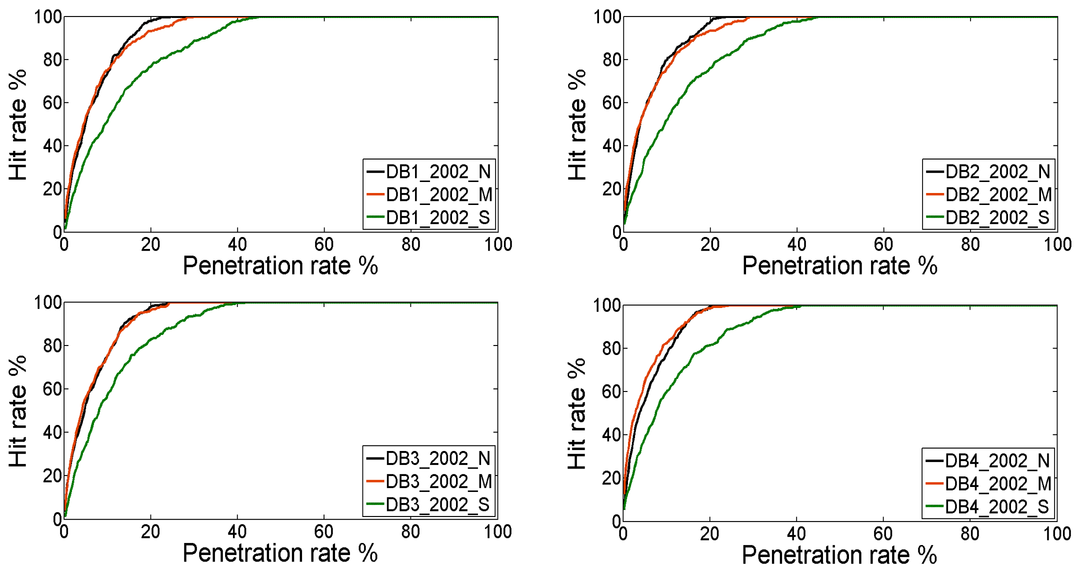

Figure 7: Performance on FVC 2002 DB1, DB2, DB3 and DB4 databases using the original minutiae data (N), 20% missing minutiae (M) and 20% spurious minutiae (S).

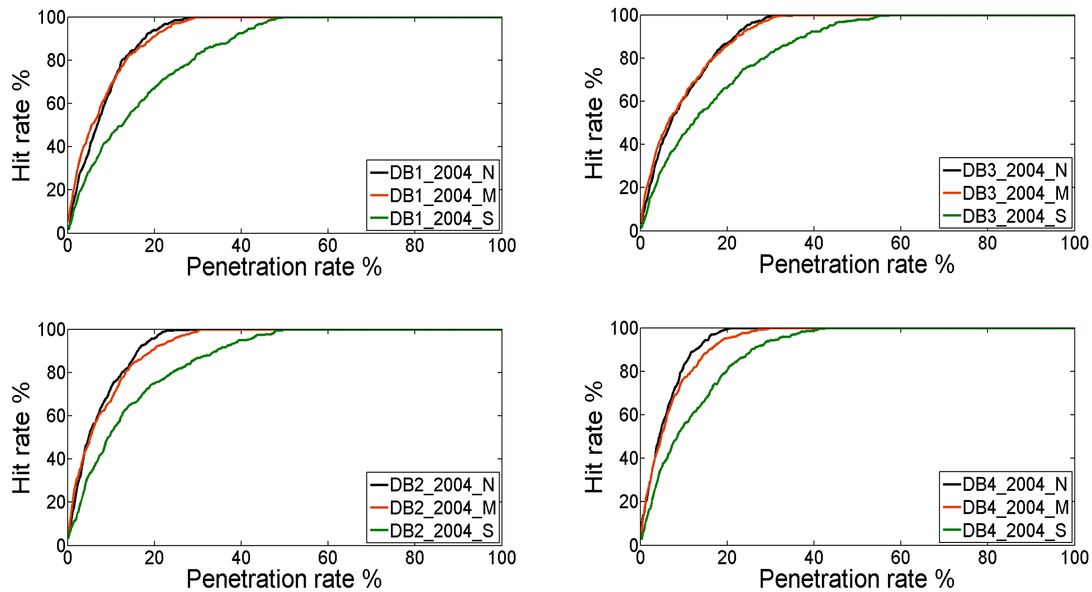

Figure 8: Performance on FVC 2004 DB1, DB2, DB3 and DB4 databases using the original minutiae data (N), 20% missing minutiae (M) and 20% spurious minutiae (S).

Table 2: Average penetration rates when using Minutiae Quadruplets, Low-order Delaunay Triangle (LoD) [7] and Minutiae Triplets [6] at hit rates of 99% and 100%. The evaluation protocol was based on [7].

	99% hit rate		100% hit rate	
FVC databases (DB1)	2002	2004	2002	2004
Minutiae Quadruplets	11.2%	11.8%	**11.8%**	**12.0%**
Low-order Delaunay Triangle [7]	**8.1%**	**10.0%**	18.1%	20.9%
Minutiae Triplets [7] (based on [6])	23.6%	27.2%	38.1%	40.9%

6. Comparison of Minutiae Quadruplets with Other Fingerprint Indexing Techniques

The proposed technique is compared with three other fingerprint indexing techniques; Minutiae triplets [6], Low-order Delaunay triangle [7] and Composite sets of reduced SIFT features [14].

The proposed technique based on quadruplets was evaluated on FVC 2002 DB1 and 2004 DB1, and compared with Liang et al.'s [7] results on minutiae triplets and low-order Delaunay triangles. For this comparison, we follow the testing scenario of Liang et al [7] and use the first three images for each subject as gallery images and the rest as probes. Table 2 shows the average penetration rates of minutiae triplets, low-order Delaunay triangle [7] and minutiae quadruplets at 99% and 100% hit rates.

The proposed technique was also compared with the method based on composite sets of reduced SIFT features [14]. For this comparison on the FVC 2000 DB2 database, the first image of each subject was enrolled in the gallery and the rest of the images were used as probes, as done in [14].

Table 3 shows the average penetration rate of Shuai et al.'s method [14] compared with minutiae quadruplets at a 100% hit rate.

Table 3: Average penetration rates when using Minutiae Quadruplets and SIFT features on FVC 2000 DB2. The evaluation protocol was based on [14].

	99% hit rate	100% hit rate
Minutiae Quadruplets	**19%**	**26%**
SIFT Features [14]	21%	91%

In Table 3, the average penetration at a hit rate of 100% is 26.33% for Minutiae Quadruplets and 91% for SIFT Features.

7. Conclusions

In this paper, the use of minutiae quadruplets has been proposed for indexing fingerprints. The consistent performance of the proposed method on the FVC 2000, 2002 and 2004 databases (set A) indicates that the proposed technique is database-independent. Experiments on fingerprints with spurious minutiae points and fingerprints with missing minutiae show that the technique is reasonably robust. The retrieval strategy is computationally inexpensive and the proposed method has small storage requirements. Further analysis is necessary to leverage the proposed technique into operational systems. Based on the experiments conducted in this work, it is apparent that minutiae quadruplets are a viable alternative to minutiae triplets for indexing.

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