Improving Recognition Performance in Multiple Enrollment Based Fingerprint Recognition Systems

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Abstract— **Multiple enrollment based fingerprint recognition systems have for long been known for good recognition accuracies. They however suffer poor matching speeds, a lot of memory consumption and the recognition accuracies are still very low; making implementation in real-world applications difficult. This paper presents a novel approach that performs prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption. A spectral minutiae based matching method and two fingerprint databases (FVC2000-DB2 and FVC2006-DB2) were used. A comparison of our results with the existing ones presented in literature shows that they are more superior. This makes it possible to design better multiple enrollment based fingerprint recognition systems with a high recognition accuracy, high matching speed and low memory consumption using our approach.**

Keywords- Multiple enrollment, Recognition Performance matching speed, memory consumption, Spectral Minutiae-based matching.

1. INTRODUCTION

In fingerprint recognition systems, it is almost infeasible to capture good quality (accurate) fingerprint images for recognition at one time. This is because, not all the required distinct fingerprint features may be collected. This can be attributed to a number of factors such as noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, low quality fingerprint images, worn-out fingerprint images, partial overlap, finger pressure and skin conditions [2], [3]. The factors mentioned above negatively affect the recognition performance/accuracy and make it hard to relay on single enrollment where one fingerprint sample is collected per individual at one time.

A number of researchers have for long proposed that enrollment of individuals using multiple fingerprint samples (multiple enrollment) would be a solution that could help in extending the information of a single enrolled fingerprint image and also ensure the reliability of each fingerprint image [2]. Multiple enrollment can also improve the recognition accuracy of the fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder [2].

From our previous research [22], [23], [24] and others (see related work), it is indeed true that multiple enrollment supports improvement in recognition accuracy of fingerprint recognition systems. We have however noted that there is still a challenge in designing and developing usable, acceptable, implementable and robust [5] multiple enrollment based fingerprint recognition systems (algorithms) that can match only high quality fingerprints amongst the many enrolled fingerprint samples, with a high matching speed, little memory consumption but still maintaining a high recognition accuracy. These challenges make it almost impossible to implement multiple enrollment based fingerprint recognition systems in real-world applications.

This paper provides a novel approach towards design of multiple enrollment based fingerprint recognition systems which greatly improves the recognition accuracy, taking into account the running time/speed as well as memory consumption; by first selecting only the good quality fingerprint images amongst the many multiple enrolled images per individual for matching.

The organization of the remaining part of the paper is as follows: Section 2 provides the related work, Section 3 provides the descriptions of the databases used, an overview of the matching method used and the proposed multiple enrollment approach. Section 4, explains how the experiments were setup and the environment in which they were implemented. In Section 5, we present the results, their discussion and give a projection of the possible future work. Section 6 concludes the paper while the last two sections provide the acknowledgements and references respectively.

2. RELATED WORK

A lot of research that has been done relating to multiple enrollment has mainly focused on combining multiple fingerprint matchers (algorithms), like in [6], [8], [10], [11], [12], [18], and in some cases combining multiple fingerprint sensors, like in [7] to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. Others like [9], [13], [14], [15], [16], [17], [19], and [20], have focused on fusion of multiple sources of information to improve recognition performance. From the analysis of the previously done research related to multiple enrollment, some of the researchers have implemented decision level fusion in fingerprint verification; whereas the majority have implemented score level fusion and others have tried to combine the two in some cases. From the literature searched, it is also evident that there is a lot of interest in combining multiple sources of biometric information to improve the recognition accuracy.

However, on top of the avenues for improving recognition accuracy, little research has concentrated on improving the matching speed of such multiple source based biometric systems, usability, memory consumption and acceptability. Although multi-modal, multi-sensor, multi-matcher/algorithm based fingerprint recognition systems improve the recognition performance, their implementation, usability, memory consumption and acceptability in real-world deployment situations may not easily be achieved; it would require more costs to acquire the necessary extra resources, implement as well as convincing and training users to adapt to them. The analyzed recognition accuracies arising from the surveyed previously done research are also still low. This was the driving force for us to embark on this research; to find better ways of designing multiple enrollment based fingerprint recognition systems.

3. DATABASE DESCRIPTIONS, MATCHING METHOD USED & THE MULTIPLE ENROLLMENT APPROACH

3.1 Database Descriptions

We used two public fingerprint databases, (i) the FVC2000-DB2 (ii) the FVC2006-DB2.

3.1.1 FVC2000-DB2 Database Description

The FVC2000-DB2 [3] database consists of fingerprint images taken from 110 people with 8 impressions collected per person generating a total of 880 fingerprints. The fingerprint images were collected from untrained people, and the collection was done in two different sessions. There were no attempts made to guarantee the least possible acquisition quality. We used set A (FVC2000-DB2-A of 100 individuals) of the whole database which contains a total of 800 fingerprints.

3.1.2 FVC2006-DB2 Database Description

FVC2006-DB2 [1] is another well-known public Fingerprint Database which we used for comparison of results in our experiments. The FVC2006-DB2 database consists of fingerprint images taken from 150 people with 12 impressions collected per person; making it a total of 1800 fingerprints. During the collection of fingerprints, there was no deliberate introduction of difficulties such as exaggerated distortion, large amounts of rotation and displacement, wet/dry impressions, etc. (as it was done in the previous editions), but the population in this database is more heterogeneous and also includes manual workers and elderly people. However, the final datasets were selected from a larger database by choosing the most difficult fingers according to a quality index, to make the benchmark sufficiently difficult for a technology evaluation. An optical sensor was used, with image size 400x560 and resolution of 569dpi. For experiments under this database, we used subset A (FVC2006-DB2-A of 140 individuals) with a total of 1680 fingerprints images.

3.2 Matching Method

This section provides a description of the matching method used.

3.2.1 Spectral munitiae-based matching

With this method [21], we first extract all the minutiae template sets from the fingerprints and store them with unique identification (ID) names. It is the extracted minutiae sets that we transform into a spectral minutiae form (referred to as Minutiae Spectrum) by representing them as a fixed-length feature vector which is invariant to translation. Within the minutiae spectrum form, rotation and scaling also become translations which can easily be compensated for. Once the transformation into a Spectral Minutiae representation is done, direct matching follows by correlation between the two Spectral images and a similarity score is generated.

3.3 The multiple Enrollment Approach

We propose a novel multiple enrollment fingerprint recognition approach which further improves recognition accuracy, the matching speed and reduces memory consumption in multiple enrollment based fingerprint recognition systems.

This approach focuses on selection prior to matching by determining good images and eliminating the bad images amongst all the multiple enrolled images of each individual. To differentiate good images from bad images amongst all the multiple enrolled samples of an individual, we count the amount of minutiae features extracted for each stored template. If a template amongst the many templates possess a high number of minutiae features extracted, it is chosen as a good image for matching else it is discarded and considered a bad image sample. This is possible because, the more the number of minutiae features extracted from an image, the more likely that image sample will be from the same individual since direct matching by correlation between the two images will have based on enough features for comparison. In this case a better similarity score is generated rather than when a bad image (possessing fewer extracted features) is matched with a good image.

This therefore implies that after the selection is done, it is only the good fingerprint image samples that are chosen during the matching (fusion) process to improve the recognition accuracy, matching speed as well as reduce on the memory consumption (This explains Algorithm two-*Alg2* functionality whose outputs are presented in the results section).

In our approach, we also set a threshold which eliminates any further low results that algorithm two could have generated hence more improvement in recognition accuracy, matching speed as well as reduction in memory consumption (This explains Algorithm three-*Alg3* whose outputs are also presented in the results section)

Algorithm one (*Alg1*) is the original algorithm as discussed in our previous work [22], [23] and performs no unique cleverness but simply matches all the multiple enrolled fingerprint image samples of each individual. It is important to note that *Alg2* and *Alg3* are subsequent modifications of *Alg1* and *Alg2* respectively.

3.3.1 Multiple Genuine Comparisons

The three algorithms (*Alg1, Alg2,* and *Alg3*) as discussed section 3.3 were designed for genuine comparisons to realize a better contrast in recognition performance as well as running time/speed improvement and reduction in memory consumption in multiple enrollment based fingerprint recognition systems.

3.3.2 *Multiple Impostor Comparisons*

Impostor comparisons usually generate very low results since we are comparing (matching) one individual's fingerprint image samples with other individuals'(as impostors) image samples in a the whole database. We also designed three algorithms (*Alg1*, *Alg2* and *Alg3*) for impostor comparisons; where *Alg2* chooses the bad image samples amongst the many enrolled samples for each other individuals' (impostors') samples, *Alg3* uses a threshold to eliminate any high results that *Alg2* could have generated and *Alg1* (the original) performs no unique cleverness during impostor matching. Although impostor matching normally generates low results, our approach continues to select bad images prior to matching to consider lower results and make allowance for a more stringent security check.

4. EXPERIMENTAL SETUP AND IMPLEMENTATION ENVIRONMENT

This section describes how the multiple enrollment experiments were set and the computational environment in which they were implemented.

4.1 *The Multiple Enrollment Experimental Setup*

In this experimental setup, different comparisons were done based on the database used. For the FVC2000-DB1 database containing 110 fingers with 8 samples per finger, each comparison was done based on five fingerprints that were selected from the dataset; with four of them as the *reference* fingerprints and one as the *test* fingerprint. Score level fusion based on Max Rule in [4] then followed by taking the maximum score amongst the four attained values. For the FVC2006-DB2-A database containing 140 fingers with 12 samples per finger, each comparison was done based on seven fingerprints that were selected from the dataset; with six of them as the *reference* fingerprints and one as the *test* fingerprint. Again, Score level fusion based on the Max Rule in [4] then followed by taking the maximum score amongst the six attained values. Below are the descriptions of the genuine and impostor pairs.

A. Genuine Pairs

For multiple genuine pair matching in the FVC2000-DB2-A databases, four fingerprints of the same person, each as a *reference* were chosen matching each of them with the fifth sample of that person as the *test* fingerprint. For the 8 samples per person, we established four permutation sets, Set1, Set2, Set3 and Set4 for multi-sample enrollment and single-sample verification. The permutation sets are provided in Table 4.1. For multiple genuine pair matching in FVC2006-DB2-A database, six fingerprints of the same person each as a *reference* were chosen, matching each of them with the seventh sample of that person as the *test* fingerprint. In this case, for the 12 samples per individual we established six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 for multi-sample enrollment and single-sample genuine verification. These permutation sets are provided in Table 4.2. All the permutation sets were randomly formulated, no specific criteria was followed.

B. Impostor Pairs

For multiple impostor pair matching in FVC2000-DB1-A and FVC2000-DB2-A databases, we chose the first sample of an identity in the database and matched it with the four multiple enrollment samples of the different identities. While for multiple impostor pair matching in FVC2006-DB2-A database, we chose the first sample of an identity in the database and matched it with the six multiple enrollment samples of the different identities.

It is important to note that the permutation sets in Table1 and Table2 were randomly formulated; there was no particular criterion followed in setting them up.

Table 4.1: FVC2000-DB2-A database permutation sets of the impressions used for multi-sample enrollment and single-sample verification

Permutation Set	Enrollment Samples	Verification Samples
Set1	1,2,3,4	5,6,7,8
Set2	1,3,5,7	2,4,6,8
Set3	1,2,7,8	3,4,5,6
Set4	1,5,6,7	2,3,4,8

Table 4.2: FVC2006-DB2-A database permutation sets of the impressions used for multi-sample enrollment and single-sample verification.

Permutation Set	Enrollment Samples	Verification Samples
Set1	1,2,3,4,5,6	7,8,9,10,11,12
Set2	1,3,5,7,9,11	2,4,6,8,10,12
Set3	1,2,3,10,11,12	4,5,6,7,8,9
Set4	1,7,8,9,10,11	2,3,4,5,6,12
Set5	1,3,5,8,10,12	2,4,6,7,9,11
Set6	1,6,7,8,9,10	2,3,4,5,11,12

4.2 *Implementation Environment*

All experiments and algorithms were implemented in MATLAB 7.12.0 (R2011a). We carried out all experiments on an Intel(R) Core(TM) i5-3230M CPU 2.60GHz, with 4GB of RAM running a 64-bit Windows 8 Pro operating system. The VeriFinger 6.0.0.7 extractor was used to extract all the minutiae templates from all the fingerprint images in all the three databases. We used the MATLAB Elapsed Time (etime) function to calculate how long the algorithms take to complete a task from the start to the end and the MATLAB Profiler feature to monitor the peak memory consumption/usage for each algorithm during computation.

5 RESULTS, DISCUSSION OF RESULTS AND FUTURE WORK

This section provides the results, their discussions and the future work.

5.1 *Experiments on the FVC2000-DB2 Fingerprint Database*

For all the three algorithms, we established four permutation sets, Set1, Set2, Set3 and Set4 for multi-sample enrollment and single-sample genuine verification. For impostor verification, we chose the first sample of an identity in the database and compared it with the four multiple enrollment samples of the different IDs.

In algorithm one-*Alg1* (original), for each permutation set, we also carried out a multi-sample enrollment and single-sample verification to check the recognition performance improvements amongst the sets. In each set we generated 400 genuine comparisons and 9900 impostor comparisons.

For the whole multiple enrollment experiment using *Alg1*, we generated 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set are shown in Table I.

5.2 Experiments on the FVC2006-DB2 Fingerprint Database

For all the three algorithms, we established six permutation sets, *Set1, Set2, Set3, Set4, Set5* and *Set6* for multi-sample enrollment and single-sample genuine verification. For impostor verification, we chose the first sample of an identity in the database and compared it with the six multiple enrollment samples of the different IDs.

In algorithm one-*Alg1* (original), for each permutation set, we also carried out a multi-sample enrollment and single-sample verification to check the recognition performance improvements amongst the sets. In each set we generated 840 genuine comparisons and 19460 impostor comparisons.

For the whole multiple enrollment experiment, we generated 140 x 6 x 6 = 5040 genuine comparisons and 140 x 139 x 6 = 116760 impostor comparisons. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set are shown in Table II.

5.1 Remarks

It is important to note that for both databases, the genuine comparisons for algorithm one (*Alg1*) were fixed because the algorithm does not perform any kind of special image selections prior to matching. For algorithm two (*Alg2*), the total genuine comparisons differ because they were generated based on the selected good quality images for matching by the algorithm. The genuine comparisons for algorithm three (*Alg3*) also differ because they were generated based on a threshold that was set to eliminate any further low results that algorithm two (*Alg2*) could have generated.

Table I provides the experimentation results on FVC2000 DB2-A databases while Table II provides the experimentation results on FVC2006 DB2-A database.

TABLE I. SUMMARY OF EXPERIMENTATION RESULTS ON FVC2000 DB2-A DATABASE

FVC 2000-DB2	**Recognition Performance**			**Running Time /Speed (sec)**			**Peak Memory Consumption(KB)**		
Permutation Set	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**
Set1	2%	1.12%	0%	337.01	207.82	167.42	960	148	16
Set2	2.25%	0.75%	0%	235.38	173.75	169.59	320	148	64
Set3	1.25%	1.09%	0%	231.75	169.10	166.51	148	92	16
Set4	2%	1.85%	0%	232.82	170.57	168.79	148	44	16

TABLE II. SUMMARY OF EXPERIMENTATION RESULTS ON FVC2006 DB2-A DATABASE

FVC 2006-DB2	**Recognition Performance**			**Running Time/Speed (sec)**			**Peak Memory Consumption(KB)**		
Permutation Set	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**	**Alg1**	**Alg2**	**Alg3**
Set1	0.95%	0.75%	0%	594.58	582.42	561.58	364	256	44
Set2	1.19%	0.76%	0%	593.40	581.42	562.91	324	192	108
Set3	1.07%	0.63%	0%	723.78	700.93	675.65	320	260	128
Set4	0.95%	0.51%	0%	704.87	588.83	578.27	320	192	148
Set5	1.19%	0.76%	0%	622.81	547.42	528.84	448	256	192
Set6	1.19%	1.02%	0%	547.95	539.18	536.16	320	260	192

5.2 Discussion of Results and Future Work

The results presented in Table I and Table II demonstrate a significant improvement in recognition performance, running time and memory consumption. Comparing algorithm one (*Alg1*) which was our previously presented algorithm in [95, 96], with algorithm two (*Alg2*) and three (*Alg3*) which are subsequent improvements of *Alg1*, we see that the recognition performance, for all the permutation sets greatly improved, whereas the matching speed and peak memory consumption drastically reduced when *Alg1* and *Alg2* were applied respectively (This can be seen from the left hand side of the Tables I and II to the right hand side). The reason for this significant improvement can be attributed to the fact that, *Alg1* in its state performs matching of all the multiple enrolled samples of the individual whether good or bad which increases the matching speed as well as the memory consumption. The more the images to match the more time it takes and the more memory it consumes. On the other hand, *Alg2* performs prior selection of only the good images of the multiple enrolled samples of the individual before matching. After selection, then matching continues for only the chosen good samples. With this, the matching speed and memory consumption greatly reduce since there are now fewer samples for matching per individual. This also applies to *Alg3*; which on top of prior selection to matching uses a threshold to eliminate any further low results that *Alg2* could have generated. Because of this further elimination, the recognition performance is to its best and the matching speed as well as the memory consumption also further reduce.

A comparative assessment of our results with the existing ones presented in literature shows that they are more superior.

The presented results are all based on minutiae matching methods for multiple enrollment based fingerprint recognition systems design. Future work can look into how other fingerprint matching methods can also be used to design multiple enrollment based recognition systems still focusing on recognition performance improvement, matching speed and memory consumption reduction. An assessment of the matching methods would also be a good venture to determine which method would be best for implementation in real world multiple enrollment based fingerprint recognition systems.

6 CONCLUSION

This research aimed at improving recognition performance in multiple enrollment based fingerprint recognition systems. We have presented a novel approach that performs prior selection of good fingerprint image samples of an individual for matching to further improve recognition performance, reduce the matching speed as well as memory consumption. The approach also uses a threshold to further eliminate bad results for a better performance accuracy improvement, matching speed and memory consumption reduction. A minutiae based matching method and two fingerprint databases were used. A comparison of our results with the existing ones presented in literature shows that they are more superior. This makes it possible to design better multiple enrollment based fingerprint recognition systems with a high recognition accuracy, high matching speed and low memory consumption using our approach.

ACKNOWLEDGMENTS

Great thanks to Ass. Prof. John Ngubiri and Ass. Prof. Florence Tushabe for their expertise and guidance during this research undertaking.

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