Evaluation of Multiple Enrollment for Fingerprint Recognition

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Abstract— **Fusion of multiple impressions resulting from multiple fingerprint enrollments is one of the ways often used to improve fingerprint recognition performance. In this research, we perform an evaluation of the effectiveness of using multiple enrollment in fingerprint recognition systems. We design a multiple enrollment algorithm and use it together with existing fingerprint recognition techniques to carry out the evaluation. Our experimentation results and evaluations show that multiple enrollment as whole outperforms single enrollment. Multiple enrollment in experiment (1) improved the recognition performance by 83% from EER[1] of 0.75% to EER of 0.13% with FVC2000-DB2, and by 79% from EER of 1.14% to EER of 0.28% with the SAS-DB2 fingerprint database. On the other hand, the multiple enrollment in experiment (2) improved the recognition performance by 71% from EER of 6.14% to EER of 1.75% with FVC2000-DB2 and improved recognition performance by 53% from EER of 14.97% to EER of 6.94% with SAS-DB2 fingerprint database.**

Keywords- Multiple enrollment, Single enrollment, Recognition Performance Improvement, Traditional Minutiae-based matching, Spectral Minutiae-based matching.

1. INTRODUCTION

The demand for higher security and more convenient operations for the case of access control and personal data protection spur intensive research, deployment and commercialization of biometric systems. Distinct from traditional identification methods, which rely on what you know (for example PIN, Password) or what you have (like key, token), a biometric system makes judgments based on what you are, and thus meets more stringent security requirements, while relieving users from the burden of remembering passwords[23]. Using fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition [23]. Acquiring accurate fingerprint images for recognition in a one-time capture is infeasible; because not all the necessary and distinguishable fingerprint information may be collected. Enrollment using multiple fingerprint samples (multiple enrollment) is a solution that can help in extending the information of a single enrolled fingerprint image, assure the reliability of each fingerprint image and also improve the recognition accuracy of a 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. However, the variability and typicality of an individual's multiple acquired fingerprints can be of concern in a fingerprint recognition system. For instance, when the with-in variance of the multiple enrolled fingerprints is too small or too large to represent the actual fingerprint variability of a given individual. This variability can be as a result of noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, etc. It is also possible that the different multiple acquired fingerprints of the same finger could certainly portray different parts of the finger's surface, hence causing the variability.

The main aim of this research is to perform an evaluation of the effectiveness of using multiple enrollment in fingerprint recognition systems. We carryout multiple enrollment and investigate the recognition performance improvements resulting from the deployment of multiple enrollment using (i) a Traditional minutiae based matching method and (ii) a Spectral Minutiae-based matching method.

The remaining part of the paper is organized as follows: Section 2 provides the related work. Section 3 provides the descriptions and characteristics of the databases used, an overview of the methods used and the multiple enrollment algorithms steps. Section 4 explains the setup of the research experiments and the implementation environment, while Section 5, provides the experimentation results and the evaluations. Section 6 provides the conclusion, discussions and future work while the last two sections provide the acknowledgements and references respectively.

2. RELATED WORK

2.1 Multi-Sample Fusion For Fingerprint recognition: The Trend

Biometric fusion with respect to fingerprints has been in use for quite a long time; mainly in the law enforcement field [23]. Due to its impact on the recognition performance of biometric systems, fusion has increasingly attracted a vast amount of research. To realize this impact, different researchers have explored the fusion approach by taking up any of the forms and implementation levels. Fusion can be carried out based on the information source chosen. First, using multiple traits as the source of information. For instance, fingerprint and face where a user would be required to swipe his finger first and then verify by presenting his face, fingerprint and voice [34] where the user swipes his finger and has to also answer some questions based on the provided challenges (see [9] for more details about a challenge-response-based voice recognition system), fingerprint and iris, fingerprint and hand geometry [33], face and speech [8, 5, 13] etc. When fingerprints are fused with other biometric traits, it is not only a higher recognition accuracy that is achieved but the system also becomes more robust to imposter attacks and also more difficult to fool. It is also possible that a number of users may not possess a particular biometric which qualifies multiple traits biometric a good option. An example of fusion research performed using a number of multiple traits is one in [26]

[1] EER: Equal Error Rate - It is the Error Rate at which the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are identical (equivalent).

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where three biometric traits; face, fingerprint and hand geometry were combined. With such a system, a high recognition performance is achieved and it is difficult for an intruder to spoof the multiple traits simultaneously. The most common levels of fusion that have been used in the multiple traits based recognition systems are score or rank levels; this is due to the differences in representations among the traits [23]. Another source of information that has often been used for fingerprint fusion is Multiple fingers of the same person, where two or more fingers of the same person are combined. For this kind of fusion, it is required to choose which fingers to be used from both hands and also in what order the users would present them at enrollment and verification. For example in the FVC2000 [22], up to four fingers were collected from each person; taking the forefinger and middle finger of both hands. Similar to fusion using multiple traits, it is not only a higher recognition accuracy that can be achieved but the fingerprint recognition system also becomes more difficult to fool. Fusion at score-level has been the most popularly used implementation level for multi-finger recognition systems; although it is also possible to fuse multiple fingers at other levels.

2.2 Recognition Performance improvement with Multi-Sample Fusion

Studies from different researchers [4, 26, 32, 21, 6, 20] show that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used. Hybrid biometric systems like one in [18] which use the face and fingerprint as primary traits together with gender, ethnicity, and height as the soft characteristics also shows a significant recognition performance improvement. In their research "*decision-level fusion in fingerprint recognition*" [25], Prabhakar and Jain show that if different fingerprint matching algorithms are combined (four algorithms were used), the overall performance is increased. Not only that, but they also show that combining multiple impressions or multiple fingers improves the verification performance of the fingerprint recognition system.

3. DATABASE DESCRIPTIONS, METHODS USED & THE MULTIPLE ENROLLMENT ALGORITHM

3.1 Database Description

We used two kinds of fingerprint databases, (i) the FVC2000-DB2 public fingerprint database and (ii) the SAS-DB2 fingerprint database.

3.1.0 FVC2000-DB2 Database Description

This is a well-known public Fingerprint Database which we used for comparison of results in order to give the public an overview of the effectiveness of multiple enrollment in Fingerprint recognition systems. The FVC2000-DB2 database consists of fingerprint images taken from 110 people with 8 impressions collected per person; making it a total of 880 fingerprints. The fingerprint images were collected from untrained people, done in two different sessions and there were no attempts made to guarantee the least possible acquisition quality. We used set A of the database which contains 100 fingers, with 8 samples per finger (in total 800 fingerprints) and we used all the 8 samples from each finger. More information about the FVC2000-DB2 database can be found at [1].

3.1.1 SAS-DB2 Database Description

This database is owned by the Signals and Systems (SAS) group at the Faculty of Electrical Engineering Mathematics and Computer Science (EEMCS) of the University of Twente in the Netherlands. The database consists of fingerprint images taken from 123 people with 12 samples per person collected from 6 different sessions and they are in resolution of 500 dpi. The U.are.U (by Digital Persona) optical sensor was used to collect the fingerprint images of this database. Up to six fingers were collected for each volunteer; the pointing finger (or forefinger), middle finger and the ring finger of both hands. There were several minutes in between after every two captures and for most persons, there was an interval of about three to five weeks between the two recordings. The images were acquired from untrained people and there was no systematic cleaning of the sensor platens after each acquisition. For all the experiments, we used fingers numbered from 1 to 100, with 12 samples per finger and we used all the 12 samples from each finger.

3.2 Methods Used

In this research we focused on use of minutiae-based matching methods. Two approaches were taken; (i) using a Traditional minutiae-based matching method and (ii) using a Spectral Minutiae-based matching method.

3.2.1 Traditional minutiae-based matching

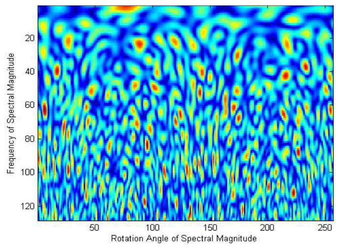
In this method, we use a commercial minutiae matcher Verifinger 6.0.0.7 for the multi-sample fingerprint enrollment and single-sample verification. We chose to use Verifinger so that we realize the fingerprint recognition performance and evaluations resulting from multiple enrollment in the commercial perspective. The fingerprint image samples of the ID(s) to be matched are loaded to Verifinger which extracts the minutiae templates and stores them with unique names. With help of the Verifinger matcher and depending on which samples to match/compare, direct matching is done between the stored minutiae templates of the enrollment samples and those chosen for verification. A matching score is generated and stored in a file for later use. For more information about the usage of Verifinger for fingerprint recognition and other capabilities, readers are referred to [2].

3.2.2 Spectral minutiae-based matching

In the academic perspective, we used the Spectral Minutiae-based matching method to realize the fingerprint recognition performance and evaluations resulting from multiple enrollment. In this method, we first extract all the minutiae templates using Verifinger 6.0.0.7 extractor and store them with unique names. The extracted fingerprint minutiae sets are then transformed into a spectral minutiae form (called Minutiae Spectrum) by representing them as a fixed-length feature vector which is invariant to translation. In 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. In the Figure 3.1(a) is the fingerprint image sample while 3.1(b), is its Spectral Minutiae representation (Minutiae spectrum) from the SAS-DB2 database. The horizontal axis of the Minutiae spectrum represents the rotation angle of the spectral magnitude while the vertical axis represents the frequency of the spectral magnitude. For more information regarding this method, we refer the readers to [35].

Figure 3.1: A Sample Fingerprint image (a) with its Spectral Minutiae representation (b)

3.1 (a) Fingerprint



3.1 (b) Minutiae Spectrum

3.3 The multiple Enrollment Algorithm

We designed a Multiple Enrolment algorithm which we used together with the methods described in section 3.2.

3.3.1 Multiple Enrollment Algorithm For Genuine Comparisons

For multiple genuine pair matching in FVC2000-DB2 database, four fingerprints of the same person, each as a reference are chosen matching each of them with the fifth sample of that person as the test fingerprint. For multiple genuine pair matching in SAS-DB2 database, six fingerprints of the same person, each as a reference are chosen matching each of them with the seventh sample of that person as the test fingerprint. The algorithm follows the following steps;

1. *Find the minutiae template storage location (database) for all IDs*
2. *Choose an ID for which multi-sample enrollment and single sample-verification is to be done*
3. *Choose the 4 (in case of FVC2000-DB2 database) or 6 (in case of SAS-DB2 database) minutiae templates of that ID for multi-sample enrollment*
4. *Search database for their existence*
5. *If template exists, load it, transform it to a Spectral minutiae template, uniquely name it and store it*
6. *Select one of the other 4 (in case of FVC2000-DB2 database) or 6 (in case of SAS-DB2 database) minutiae templates (samples) of that ID for single-sample verification*
7. *Steps 4 and 5 are repeated*
8. *Direct Spectral Minutiae matching between the two stored spectral minutiae templates follows and a genuine matching score generated.*
9. *Store the Genuine score in a matrix*
10. *Select another minutiae template (sample) of that ID for single-sample verification*
11. *Repeat steps 7 to 9*
12. *Repeat steps 10 and 11 for all other samples (Spectral minutiae templates) of that ID for single-sample verification*
13. *Choose the maximum score amongst the 4 scores (in case of FVC2000-DB2 database) or the 6 scores (in case of SAS-DB2 database) and store it in a matrix*
14. *Choose another ID for which multi-sample enrollment and single sample-verification is to be done*
15. *Repeat steps 3 through 14 until the last ID in database*

3.3.2 Multiple Enrollment Algorithm For Impostor Comparisons

For multiple impostor pair matching in FVC2000-DB2 database, we chose the first sample of an identity (ID) in the database and matched it with four multiple enrollment samples of the different identities (IDs). While for multiple impostor pair matching in SAS-DB2 database, we chose the first sample of an identity (ID) in the database and matched it with the six multiple enrollment samples of the different identities (IDs). The algorithm follows the steps below:

1. *Find the minutiae template storage location (database) for all IDs*
2. *Choose an ID (ID1) to use for enrollment*
3. *Choose a different ID (ID2) for impostor matching*
4. *Select the first minutiae template (sample) of ID1 for enrollment*
5. *Search database for its existence*
6. *If template exists, load it, transform it to a Spectral minutiae template, uniquely name it and store it*
7. *Select one of the 4 (in case of FVC2000-DB2 database) or 6 (in case of SAS-DB2 database) minutiae templates (samples) of ID2 that were used in multi-sample enrollment, for impostor verification*
8. *Steps 5 and 6 are repeated*
9. *Direct Spectral Minutiae matching between the two stored spectral minutiae templates follows and an Impostor matching score generated.*
10. *Store the Impostor score in a matrix*
11. *Select another Spectral minutiae template (sample) of ID2 for verification*
12. *Repeat steps 8 to 10*
13. *Repeat steps 11 and 12 for all other samples (Spectral minutiae templates) of ID2 for verification*
14. *Choose the maximum score amongst the 4 scores (in case of FVC2000-DB2 database) or the 6 scores (in case of SAS-DB2 database) and store it in a matrix*
15. *Choose another different ID (ID2) for impostor matching*
16. *Repeat steps 7 to 15 until last ID2 in database (excluding Current ID1)*
17. *Choose another ID (ID1) to use for enrollment*
18. *Repeat steps 4 through 17 for all IDs*

4. EXPERIMENTAL SETUP

We setup two test cases using both methods

4.1 Single Enrollment Test case

In this test case, each comparison is done based on two fingerprints that are selected from the dataset; with one as the *reference* fingerprint and the other as the *test* fingerprint. The description of the genuine and impostor pairs are as follows:

i. Genuine Pairs

For single genuine pair matching, we used all the possible combinations; matching each of the other samples (*test* fingerprints) of the same person with the first fingerprint sample of that person as the *reference*.

ii. Impostor Pairs

For single impostor pair matching, we chose one sample (the first) from each identity in the database. The single enrollment test case was included as part of this research to provide a basis for making a comparison and an evaluation of test case (ii) with regard to the recognition performances achieved.

4.2 Multiple Enrollment Test Case

In this test case, different comparisons were done based on the database used. For the FVC2000-DB2 database containing 100 fingers with 8 samples per finger, each comparison was done based on five fingerprints that were selected from the dataset; with four as the reference fingerprints and one as the test fingerprint. Score level fusion based on Max Rule in [27] then followed by taking the maximum score amongst the four attained values. While for the SAS-DB2 database using 100 fingers with 12 samples per finger, each comparison was done based on seven fingerprints that were selected from the dataset; with six as the reference fingerprints and one as the test fingerprint. Score level fusion based on Max Rule in [27] then followed by taking the maximum score amongst the six attained values. Below are the descriptions of the genuine and impostor pairs.

i Genuine Pairs

For multiple genuine pair matching in FVC2000-DB2 database, 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 (in Table 4.1) for multi-sample enrollment and single-sample verification. For the SAS-DB2 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. For the 12 samples per individual we established six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 (in Table 4.2) for multi-sample enrollment and single-sample genuine verification.

ii Impostor Pairs

For multiple impostor pair matching in FVC2000-DB2 database, 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 SAS-DB2 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. There was no particular criterion followed in setting up the permutation sets in both Table 4.1 and Table 4.2; they were all randomly formulated.

Permutation Set	Enrollment	Genuine Verification
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 4.1: FVC2000-DB2 database permutation sets of the impressions used for multi-sample enrollment and single-sample verification

Permutation Set	Enrollment	Genuine Verification
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

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

4.3 *Implementation Environment*

We implemented all the methods and algorithms in MATLAB R2010a. All experiments were carried out on an Intel(R) Pentium(R) D CPU 2.80GHz with 2.00GB of RAM running a 64-bit Windows 7 Enterprise Operating System and the Verifinger 6.0.0.7 extractor [2] was used to extract the minutiae templates from all the fingerprint images in both databases.

5 EXPERIMENTATION RESULTS AND EVALUATIONS

This section discusses the results and evaluations.

5.1 *Experiments on the FVC2000-DB2 Fingerprint Database*

5.1.1 *Using Traditional Minutiae-based Matching*

In this experiment, the VeriFinger 6.0.0.7 matcher was used for fingerprint matching to attain the similarity scores. The fingerprint samples from ID 1 to 100 were used for testing, each contributing all the 8 samples. In the single-sample enrollment test case, we used all the possible combinations for the genuine comparisons and for imposter comparisons; we used the first sample of each ID in the database. Therefore, we generated 100 x ((8 x 7)/2) = 2800 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons with an EER of 0.75%. 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. For each permutation set, we did a multi-sample enrollment and single-sample verification to realize the recognition performances amongst the sets. In each set we generated 400 genuine comparisons and 9900 impostor comparisons. We attained the following EERs: 0.25%, 0%, 0.25% and 0%, respectively for Set1, Set2, Set3 and Set4. The whole multiple enrollment experiment generated 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons with an EER of 0.13%.

5.1.2 *Using Spectral Minutiae-based Matching*

In this experiment, the similarity scores were generated by direct spectral minutiae matching. We used all the possible combinations for the genuine comparisons in the single-sample enrollment test case and for imposter comparisons; we used the first sample of each ID in the database. In total, we generated 100 x ((8 x 7)/2) = 2800 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons and an EER of 6.14% was attained. For multi-sample enrollment test case four permutation sets, Set1, Set2, Set3 and Set4 were established four 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. For each permutation set, we also carried out a multi-sample enrollment and single-sample verification to check the recognition performances amongst the sets. In each set we generated 400 genuine comparisons and 9900 impostor comparisons and the following EERs were attained: 2.0%, 2.25%, 1.25% and 2.0%, respectively for Set1, Set2, Set3 and Set4. The whole multiple enrollment experiment generated 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons with an EER of 1.75%. Table I provides a summary of the experimentation results mentioned above.

5.2 *Experiments on the SAS-DB2 Fingerprint Database*

5.2.1 *Using Traditional Minutiae-based Matching*

In this experiment, the VeriFinger 6.0.0.7 matcher was used for fingerprint matching to attain the similarity scores. The fingerprint samples from ID 1 to 100 were used for testing, each contributing all the 12 samples. For the single-sample enrollment test case, we used all the possible combinations for the genuine comparisons. And for imposter comparisons we used the first sample of each ID in the database. This in total resulted in 100 x ((12 x 11)/2) = 6600 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons. An EER of 1.14% was achieved. 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 also chose the first sample of an identity in the database and compared it (however this time) with the six multiple enrollment samples of the different IDs. For each permutation set, we performed a multi-sample enrollment and single-sample verification to see the recognition performances amongst the sets. For each set we generated 600 genuine comparisons and 9900 impostor comparisons and we achieved the following EERs: 1.0%, 0%, 0.33%, 0%, 0% and 0.33%, respectively for Set1, Set2, Set3, Set4, Set5 and Set6. The whole multiple enrollment experiment generated 100 x 6 x 6 = 3600 genuine comparisons and 100 x 99 x 6 = 59400 impostor comparisons with an EER of 0.28%.

5.2.2 *Using Spectral Minutiae-based Matching*

In this experiment, the similarity scores were attained by direct spectral minutiae matching. For single-sample enrollment, we used all the possible combinations for the genuine comparisons and we used the first sample of each ID in the database for the imposter comparisons. In total, we generated 100 x ((12 x 11)/2) = 6600 genuine comparisons and ((100 x 99)/2) = 4950 impostor comparisons. We attained an EER of 14.97%. For the multi-sample enrollment test case, six permutation sets, Set1, Set2, Set3, Set4, Set5 and Set6 were formulated for multi-sample enrollment and single-sample genuine verification. For impostor verification, we similarly chose the first sample of an identity in the database and compared it with the six multiple enrollment samples of the different IDs. For each permutation set, we also carried out a multi-sample enrollment and single-sample verification to check the recognition performances amongst the sets. In each set we generated 600 genuine comparisons and 9900 impostor comparisons and the following EERs were attained: 9.67%, 5.67%, 7.0%, 6.5%, 5.67% and 6.5%, respectively for Set1, Set2, Set3, Set4, Set5 and Set6. The whole multiple enrollment experiment generated 100 x 6 x 6 = 3600 genuine comparisons and 100 x 99 x 6 = 59400 impostor comparisons and an EER of 6.94%. Table II provides a summary of the experimentation results mentioned above.

TABLE I. SUMMARY OF FVC2000-DB2 EXPERIMENTATION RESULTS

Matching Method	Single Enrollment	Multiple Enrollment				
		Set1	Set2	Set3	Set4	Overall
Traditional Minutiae Based	0.75%	0.25%	0%	0.25%	0%	0.13%
Spectrtal Minutiae Based	6.14%	2.0%	2.25%	1.25%	2.0%	1.75%

TABLE II. SUMMARY OF SAS-DB2 EXPERIMENTATION RESULTS

5.1 *Evaluations*

	Single Enroll ment	Multiple Enrollment						
		Set1	Set2	Set3	Set4	Set5	Set6	Overall
Traditional Minutiae Based	1.14%	1.0%	0%	0.33 %	0%	0%	0.33 %	0.28%
Spectrtal Minutiae Based	14.97%	9.67 %	5.67 %	7.0%	6.5 %	5.67 %	6.5%	6.94%

5.1.1 *FVC2000-DB2 Database*

5.1.1.1 *Using Traditional Minutiae-based Matching*

Our results show that multiple enrollment per set outperformed single enrollment. Single enrollment with this method achieved an EER of 0.75% while the EERs for individual set multiple enrollment were: 0.25%, 0%, 0.25% and 0% respectively for Set1, Set2, Set3 and Set4. Similarly, the overall multiple enrollment recognition performance of EER 0.13% outperformed the single enrollment performance of EER 0.75%.

5.1.1.2 *Using Spectral Minutiae-based Matching*

Here, multiple enrollment per set using this matching method also outperformed single enrollment. For this method, single enrollment attained an EER of 6.14% while EERs of: 2%, 2.25%, 1.25% and 2.0% were respectively achieved for Set1, Set2, Set3 and Set4 using multiple enrollment. The overall multiple enrollment recognition performance of EER 1.75% also outperformed the single enrollment one of EER 6.14%.

5.1.2 *SAS-DB2 Database*

5.1.2.1 *Using Traditional Minutiae-based Matching*

The recognition performance attained in each set outperformed the one in single enrollment. EERs of 1.0%, 0%, 0.33%, 0%, 0% and 0.33%, were respectively achieved for Set1, Set2, Set3, Set4, Set5 and Set6 using multiple enrollment, compared to the 1.14% EER attained from single enrollment. The overall, multiple enrollment recognition performance of EER 0.28% also outperformed the EER of 1.14% resulting from the single enrollment experiment.

5.1.2.2 *Using Spectral Minutiae-based Matching*

In this experiment, multiple enrollment per set also outperformed the single enrollment performance. For the individual sets, the EERs attained using multiple enrollment were: 9.67%, 5.67%, 7.0%, 6.5%, 5.67% and 6.5%, respectively for Set1, Set2, Set3, Set4, Set5 and Set6 compared to the 14.97% EER resulting from single enrollment. On the other hand, the overall multiple enrollment recognition performance of 6.94% also outperformed the single enrollment performance of ERR 14.97%.

5.2 *Performance Imrpovement*

We performed an objective evaluation of multiple enrollment by considering the performance improvement in matching accuracy using both matching methods. Multiple enrollment using method (i) resulted in a 83% improvement in recognition rate over a set of 800 fingerprint images in FVC2000-DB2 database and a 79% improvement in recognition rate over a set of 1200 fingerprint images in SAS-DB2 database. On the other hand, multiple enrollment using method (ii) results in a 71% improvement in recognition rate over a set of 800 fingerprint images in FVC2000-DB2 database and a 53% improvement in recognition rate over a set of 1200 fingerprint images in SAS-DB2 database. Table III provides a summary of the experimentation results together with the performance improvements achieved.

TABLE III. EXPERIMENTATION RESULTS AND PERFORMANCE IMPROVEMENT

Matching Method	Fingerprint Database	Single Enrollment	Multiple Enrollment	Performance Improvement
Traditional Minutiae Based	FVC2000-DB2	0.75%	0.13%	83%
	SAS-DB2	1.14%	0.28%	79%
Spectrtal Minutiae Based	FVC2000-DB2	6.14%	1.75%	71%
	SAS-DB2	14.97%	6.94%	53%

5.3 *Comparison of Results*

Comparing with other researchers [36-45] who have carried out multi-sample/model fusion (with some having multiple enrollment) using minutiae as the desirable identification feature; our results outperform theirs in terms of Equal Error Rates (EER). This clearly shows that our algorithms are more superior than the ones discussed in [36-45]. However, we did not consider recording the processing time for feeding so many fingerprints and acquiring results; this was left for future work.

6 CONCLUSION

The purpose of this research was to perform an evaluation on the effectiveness of deploying multiple enrollment in fingerprint recognition systems. A multiple fingerprint enrollment algorithm was designed and used together with existing fingerprint recognition techniques. Two matching methods and two databases were used. Our experimentation results and evaluations show that multiple enrollment as whole out performs single enrollment and the overall performance improved by more than a 50% recognition rate. For a typical biometric security system, an improvement in recognition rate of more than 50% is a great achievement. This performance improvement can be attributed to the fact that, the source of information becomes large making it is easy to compensate for outliers such as rotations, noise, displacements, etc. It is also true that the lesser the outliers, the better the recognition performance.

6.1 Discussions and Future Work

Despite of the great improvement in recognition rate, multiple enrollment still comes with challenges. One is the high storage demand and a slow matching/comparison speed. The comparison and computation time are really too high for a seamless real-time fingerprint recognition system. The minutiae-based methods themselves have a relatively slow comparison speed; although their recognition performance is very good most especially for good quality fingerprints. Future work should aim at other methods/algorithms to check both performance improvement and comparison speed while using multiple enrollment for real-time fingerprint recognition systems. Also, not all the input fingerprint samples corresponding to an individual were of good quality. Extraction of desirable features from the low quality fingerprint samples can also greatly affect the recognition performance. A good multi-sample fusion scheme to help in such a situation would be one that could automatically allocate lower weight values to low quality fingerprint samples and higher weight values to good quality fingerprint samples and then later choose ones with higher weight values for fusion. User cooperation and training would also be crucial for a typical security biometric system. All the experiments in this research were performed on data from un-trained persons. Performance from multiple enrollment can even be better when the users are trained.

ACKNOWLEDGMENTS

Great thanks to Dr. ir. R.N.J. Veldhuis, Dr. ir. H. Xu, for their great expertise during this research.

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