Combined Feature Level and Score Level Fusion Gabor Filter-Based Multiple Enrollment Fingerprint Recognition

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***Abstract*— Minutiae-based fingerprint matching methods suffer difficulty in automatically extracting all minutiae points due to failure to detect the complete ridge structures of a fingerprint, as well as describing all the local ridge structures as minutiae points. These make matching a difficult process for example, the case where two fingerprints have different numbers of uncaptured minutiae points and hence negatively affecting recognition performance, matching speed and memory consumption. Gabor filter-based matching methods can capture both the local and global details of a fingerprint which qualifies them to be a possible alternative due to their rich features. This paper presents a Combined Feature Level and Score Level Fusion Gabor filter-based approach; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. We compared the Combined Feature Level and Score Level Fusion Gabor filter-based multiple enrollment fingerprint recognition method with a spectral minutiae-based method using two fingerprint databases; FVC 2000-DB2-A and FVC 2006-DB2-A. Our results indicate that there is a significant percentage increase brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The percentage increases in the FVC 2000-DB2-A were 86.45%, 98.01% and 87.82%, while those in the FVC 2006-DB2-A were 79.71%, 97.07% and 85.88% respectively for recognition performance improvement, matching speed improvement and memory consumption reduction. The outstanding results attained from the proposed approach leave no room for deployment in real world multiple enrollment fingerprint recognition applications that require better recognition performance, good matching speed and reduced memory consumption.**

Keywords*— Feature level fusion, Gabor Filter-based matching, Matching speed, Memory consumption, Multiple enrollment, Recognition performance, Score Level Fusion, Spectral Minutiae-based matching.

I. INTRODUCTION

In our previous work [1], it was noted that a number of researchers have concentrated on minutiae-based matching methods while setting up multiple enrollment based fingerprint recognition systems. Matching methods such as correlation based like, [2],[3],[4],[5],[6] and pattern based methods like, [7],[8],[9] have been generally used for verification, indexing and identification in fingerprint recognition; but rarely implemented in multiple enrollment based fingerprint recognition systems. The challenges of minutiae-based matching methods as pointed out in [10] are; difficulty in automatically extracting all minutiae points due to the failure to detect the complete ridge structures of a fingerprint, as well as describing all the local ridge structures as minutiae points. These make matching a difficult process for example the case where two fingerprints have different numbers of uncaptured minutiae points. We proposed a non-minutiae based technique (Gabor filtering) which is known to be rich in terms of distinguishing features and an alternative since it captures both the local and global details in a fingerprint. Their resultant representation is scale, translation and rotation invariant and they produce short fixed length feature vectors, which makes them appropriate for indexing, faster fingerprint matching and storage on smaller devices [11]. The above mentioned, was the first of the kind to implement a Gabor Filter-Based verification multiple enrollment based fingerprint recognition system. Although the minutiae-based method outperformed the proposed Gabor filter-based method, the results attained from the later were promising for implementation and helpful in designing multiple enrollment based fingerprint systems. However, there were still challenges in the proposed approach; the recognition performance was still poor, the matching speed/running time was bad and memory consumption was at the worst.

This paper presents an improved approach, the combined feature level and score level fusion Gabor filter-based method; the first of the kind to implement a verification multiple enrollment based fingerprint recognition system. The proposed combined feature level and score level fusion technique significantly improves the recognition performance, the running time/matching speed and reduces the memory consumption.

The remaining part of this paper is organized as follows: Section 2 provides the related work, Section 3 provides the descriptions of the databases used, the matching methods used and an overview of the algorithm used. In Section 4 we

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explain how the experiments were setup and the environment in which they were implemented. In Section 5, we present the results, their discussion and the anticipated future work. Section 6 concludes the paper while the last two sections provide the acknowledgements and references respectively.

II. RELATED WORK

W Fusion in biometrics has been applied in fingerprint recognition systems since long [12]. Fusion takes on various forms depending on the choice of the source of information made [13]. One of the commonly used forms of fusion is the combination of multiple traits; for example, fingerprint and face, fingerprint and voice [7],[14], fingerprint and iris, fingerprint and hand geometry [15], face and speech [16, 17, 18], face, fingerprint and hand geometry [19] and many more. It is noted that fusion of fingerprints with other biometric traits not only results in a higher recognition accuracy but also adds on the security of the system. It becomes more robust to imposter attacks, difficult to fool and it also works as a substitute where a user may not have a certain biometric hence qualifying multiple traits biometric a good choice. The other commonly used form of fusion is combining multiple fingers of the same person like in [20]. In the multiple traits fusion form, the comments levels of fusion that have been used are score and rank levels because of the difference in representation among the traits [12]. For the multiple finger form of fusion, score level fusion has been commonly implemented. The approach in this paper uses a combination of feature level and score level fusion based on multiple instances of the same biometric trait (fingerprint) to overcome such challenges. Feature level fusion can help to prevent modification of the biometric template since it is not only one feature but a combination of random features which the attacker may not be able to tell.

Feature level fusion has been deployed by a number of researchers to improve recognition performance in multimodal/multibiometric systems. Arun and Rohin in [22], [23], use feature level fusion to fuse hand and face biometrics, Dakshina et al in [38] fused fingerprint and ear biometrics to attain a robust performance while A. Rattani et al in [39] also used feature level fusion to fuse face and fingerprint biometrics to improve recognition accuracy. Adams and David in [24] applied feature level fusion on multiple Gabor filters to produce a single fused feature which on comparison/matching using normalized hamming distance improved efficiency in identifying individual’s palmprints. Adams et al [40], further made improvements in verification and identification when they fused multiple elliptical Gabor filters of a palmprint using feature level fusion. Poonam and Zope [41], used Gabor filter based multimodal biometric system where they use feature level fusion to fuse fingerprint and face Gabor filters to reduce computational complexity but improve accuracy. Gayathri and Ramamoorthy [42] use feature level fusion to fuse Gabor texture from palmprint and iris to improve recognition accuracy. Fathima and Poornima [43] use feature level fusion to fuse iris and ear features performance in their multimodal biometric authentication system. Navdeep and Gaurav [44] also fuse palmprint and fingerprint using feature level fusion to obtain a better system recognition performance. Jacob et al [37] use feature level fusion to fuse features extracted from one modality/same biometric trait (multiple fingerprints) of an individual to obtain an improvement in matching performance/processing time. N. Vinay Kumar et al [45], Use feature level fusion for classifying many logos to achieve a more accurate classification compared to a single logo feature. The Euclidian distance between the test logos and stored logos is calculated and the minimum Euclidian distance amongst all is used to classify the logo image as a member of the class. Other researchers like [25], [26], [27], [28], [29], [30], [31], [32], [33],[34],[35] and [36], have also used feature level fusion to improve recognition performance in multimodal biometric systems. Our analysis shows that feature level fusion has picked up interest from various researchers as compared to before when score level fusion and decision level fusion were the most commonly used. It has also been noted that most of the researchers have concentrated on multiple traits while using feature level fusion. These approaches suffer incompatibility due to difference in feature sets, feature space and feature vector length [37] making it challenging to fuse or even to trust those fused feature vectors that result from padding to make the feature vector lengths similar. Our approach uses Gabor filters focusing on combining both feature level fusion and matching score level fusion using multiple instances of the same biometric trait (fingerprint).

III. DATABASE DESCRIPTIONS, MATCHING METHODS AND ALGORITHM USED

A. Database Descriptions

Two public (internationally known) fingerprint databases namely; FVC2000-DB2 [46] and FVC2006-DB2 [47], were used.

1) The FVC2000-DB2 Database

This database comprises fingerprint image samples taken from 110 people with 8 impressions per person generating a total of 880 fingerprints. These multiple samples were collected from untrained people, there were no attempts made to guarantee the least possible acquisition quality and the collection was done in two different sessions. However, for all experiments in this paper, set A (FVC2000-DB2-A of 100 individuals) of the whole database which contains a total of 800 fingerprints was used.

2) The FVC2006-DB2 Database

This database comprises fingerprint image sample taken from 150 people with 12 impressions per person generating 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. For all experiments in this paper, subset A (FVC2006-DB2-A of 140 individuals) with a total of 1680 fingerprints images was used.

B. The Matching Methods and Algorithm Used.

This section presents a description of the matching methods used throughout all the experiments.

1) Spectral Minutiae-based matching.

In this method [48], all the minutiae template sets from the fingerprint image sample are first extracted and then stored with unique identification (ID) names. The extracted minutiae sets are then transformed 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.

2) Combined Feature Level and Score Level Fusion Gabor Filter-based matching.

In this method, the Gabor features of all input fingerprint image samples are first extracted as in [49]. Column vectors consisting of the Gabor features of the input fingerprint image samples are created. These feature vectors are normalized to zero mean and unit variance (to remove any noise originating from sensors as well as the grey level background which maybe generated because of the finger pressure differences), and then stored with unique identification (ID) names. A random feature level fusion of the feature vectors generated from the different fingerprints is performed. Two feature vectors are concatenated and feature selection done in preparation for final matching/comparison (see algorithm section 3). It is at this stage after feature selection that multiple enrollment and single sample verification is done. Direct matching is done by calculating the Euclidean distance (using Equation (1)) between the two newly fused feature vectors; originating from the two randomly fused fingerprint feature vectors. Based on this Euclidean distance(Ed) value obtained, a matching score is computed such that; the higher the Euclidean distance(Ed), the lower the matching score and vice versa. The score is computed and standardized as shown in Equation (2) [21]. Finally, score level fusion based on the Max Rule in [15] follows by taking the maximum score amongst the attained values.

x and y are the randomly fused feature vectors; fffv1 and fffv2 respectively originating from the two fingerprint samples to be compared. The formula is a standard MATLAB function.

$$\text{Euclidean Distance}(Ed) = \text{norm}(x - y) \quad (1)$$

Ed is the Euclidean distance between the two randomly fused feature vectors; fffv1 and fffv2 respectively originating from the two fingerprint samples to be compared.

$$\text{Matching score} = 1/((1 + Ed)) \quad (2)$$

3) The Algorithm Used

Let ffvID_n = {ffv1_1, ffv1_2, ffv1_3,…, ffv1_n} represent an individual's fingerprint feature vectors; where (i) ffvID = 1:100 and n = 1:8, are the feature vectors (ffv) extracted from 100 individuals (IDs) 8 copies each for FVC 2000-DB2-A database and (ii) ffvID = 1:140 and n = 1:12; are feature vectors (ffv) extracted from 140 individuals (IDs) 12 copies each, for the FVC 2006-DB2-A database. The fused fingerprint feature vector fffvID_n = {fffv1_1, fffv1_2, fffv1_3 … fffv1_n} is obtained by concatenating two fingerprint feature vectors and performing feature selection to obtain the final fused feature vector. Table I and Table II represent sample feature level fusion for one individual in both databases respectively.

TABLE I
SAMPLE FEATURE LEVEL FUSION FOR ONE INDIVIDUAL (ID=1) IN THE FVC 2000-DB2-A DATABASED

Fingerprint Feature Vector	Randomly Selected Fingerprint Feature Vector	Fused Fingerprint Feature Vector
ffv1_1	ffv1_2	fffv1_1
ffv1_2	ffv1_3	fffv1_2
ffv1_3	ffv1_4	fffv1_3
ffv1_4	ffv1_5	fffv1_4
ffv1_5	ffv1_6	fffv1_5
ffv1_6	ffv1_7	fffv1_6
ffv1_7	ffv1_8	fffv1_7
ffv1_8	ffv1_1	fffv1_8

TABLE II
SAMPLE FEATURE LEVEL FUSION FOR ONE INDIVIDUAL (ID=1) IN THE FVC 2006-DB2-A DATABASED

Fingerprint Feature Vector	Randomly Selected Fingerprint Feature Vector	Fused Fingerprint Feature Vector
ffv1_1	ffv1_2	fffv1_1
ffv1_2	ffv1_3	fffv1_2
ffv1_3	ffv1_4	fffv1_3
ffv1_4	ffv1_5	fffv1_4
ffv1_5	ffv1_6	fffv1_5
ffv1_6	ffv1_7	fffv1_6
ffv1_7	ffv1_8	fffv1_7
ffv1_8	ffv1_9	fffv1_8
ffv1_9	ffv1_10	fffv1_9
ffv1_10	ffv1_11	fffv1_10
ffv1_11	ffv1_12	fffv1_11

IV. EXPERIMENTAL SETUP AND IMPLEMENTATION ENVIRONMENT

In this section, the setup of both the minutiae-based and the combined Feature level and Score Level Gabor filter-based multiple enrollment experiments is described as well as the computational environment in which they were implemented.

A. The Multiple Enrollment Experimental Setup

Based on the database, different comparisons were performed during the experimental setup. In the FVC2000-DB2-A database which comprises 100 fingers with 8 samples per finger, each comparison was performed based on five fingerprints that were selected from the feature level fused dataset. In this database, four of the five fingerprints were used as the reference fingerprints and one as the test fingerprint. Score level fusion based on Max Rule in [15] then followed by taking the maximum score amongst the four attained values. In the FVC2006-DB2-A database which comprises 140 fingers with 12 samples per finger, each comparison was performed based on seven fingerprints that were selected from the feature level fused dataset. However for this database, six of the seven fingerprints were used as the reference fingerprints and one as the test fingerprint. Again, Score level fusion based on the Max Rule in [15] then followed by taking the maximum score amongst the six attained values. In the section below a full description of the genuine and impostor pairs used for the multiple enrollment experiments is provided.

a). Genuine Pairs

For multiple genuine pair matching in the FVC2000-DB2-A database, four permutation sets were established (shown in Table III) after feature level fusion; Set1, Set2, Set3 and Set4 for multi-sample enrollment and single-sample verification. Based on the 8 samples per person, 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. On the other hand, for multiple genuine pair matching in FVC2006-DB2-A database, six permutation sets were established (shown in Table IV) after feature level fusion; Set1, Set2, Set3, Set4, Set5 and Set6 for multi-sample enrollment and single-sample genuine verification. Based on the 12 samples per person, 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. There was no particular procedure followed in creating the permutation sets. All the permutation sets were randomly formed.

b). Impostor Pairs

For multiple impostor pair matching in FVC2000-DB2-A database, the first sample of an identity in the database was chosen and matched with the four multiple enrollment samples of the different identities. While for multiple impostor pair matching in FVC2006-DB2-A database, the first sample of an identity in the database was selected and matched with the six multiple enrollment samples of the different identities.

TABLE III
FVC 2000-DB2-A DATABASE PERMUTATION SETS OF THE IMPRESSIONS USED FOR MULTI-SAMPLE ENROLLMENT AND SINGLE SAMPLE VERIFICATION

Permutation Sets	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 IV
FVC 2006-DB2-A DATABASE PERMUTATION SETS OF THE IMPRESSIONS USED FOR MULTI-SAMPLE ENROLLMENT AND SINGLE SAMPLE VERIFICATION

Permutatio n Sets	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

B. The Implementation Environment

All the experimentations and algorithms in this research were implemented in MATLAB 7.12.0 (R2011a). The researchers 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. For the minutiae-based method, the VeriFinger 6.0.0.7 extractor was used to extract all the minutiae templates from all the fingerprint images in all the two databases. For the combined feature level and score level fusion Gabor Filter-based method, the Gabor filter extractor in [49] was used. The TIC_TOC MATLAB elapsed time function was used to calculate how long the algorithms took to complete a task from the start to the end. On the other hand, the MATLAB Profiler feature was used to monitor the peak memory consumption/usage for each algorithm (Minutiae-based and combined feature level and score level fusion Gabor filter-based) during all the computations/experimentations.

V. RESULTS, DISCUSSIONS AND FUTURE WORK

In this section, the authors present the results, their discussion and the future work.

A. Experiments on the FVC2000-DB2-A Fingerprint Database

For this database, four permutation sets (Set1, Set2, Set3, and Set4) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, the researchers performed a multi-sample enrollment and single-sample verification to check the recognition performance amongst the sets. In each set 400 genuine comparisons and 9900 impostor comparisons were generated. For the whole multiple enrollment experiments in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, 100 x 4 x 4 = 1600 genuine comparisons and 100 x 99 x 4 = 39600 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method are shown in Table V.

B. Experiments on the FVC2006-DB2-A Fingerprint Database

For this database, six permutation sets (Set1, Set2, Set3, Set4, Set5 and Set6) were formulated for multi-sample enrollment and single-sample genuine verification as well impostor verification. For each permutation set in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, a multi-sample enrollment and single-sample verification was performed to check the recognition performance amongst the sets. In each set 840 genuine comparisons and 19460 impostor comparisons were generated. For the whole multiple enrollment experiments in in both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method, 140 x 6 x 6 = 5040 genuine comparisons and 140 x 139 x 6 = 116760 impostor comparisons were generated. The attained Equal Error Rates (EERs), matching speeds, and peak memory consumptions per set for both the minutiae-based method and the combined feature level and score level fusion Gabor Filter-Based method are shown in Table VI.

TABLE V
SUMMARY OF EXPERIMENTATION RESULTS ON FVC 2000-DB2-A DATABASE

FVC 2000-DB2-A	**Recognition Performance (EER) %**			**Running Time /Speed (Secs)**			**Peak Memory Consumption (kbs)**		
Permutation Sets	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**
Set1	2%	8.5%	0.26%	337.01	1609.45	5.29	960	2696	44
Set2	2.25%	1.25%	0.00%	235.38	1561.27	5.41	320	1892	44
Set3	1.25%	2.5%	0.76%	231.75	1588.27	5.30	148	1892	64
Set4	2%	3.25%	0.00%	232.82	1580.76	4.59	148	2084	40

TABLE VI
SUMMARY OF EXPERIMENTATION RESULTS ON FVC 2006-DB2-A DATABASE

FVC 2006-DB2-A	**Recognition Performance (EER) %**			**Running Time /Speed (Secs)**			**Peak Memory Consumption (kbs)**		
Permutation Sets	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter- Based**	**Minutiae-Based**	**Original Gabor Filter-Based**	**Combined Feature Level and Score Level Gabor Filter-Based**
Set1	1%	6.7%	0.24%	594.58	13889.48	20.62	364	5536	64
Set2	1.19%	7.50%	0.00%	593.40	13767.57	15.49	324	5404	40
Set3	1.07%	5.2%	0.37%	723.78	10336.05	22.88	320	5024	44
Set4	1%	5.83%	0.24%	704.87	10110.41	20.88	320	4828	40
Set5	1%	5.4%	0.12%	622.81	10734.52	14.21	448	5216	44
Set6	1.19%	5.95%	0.36%	547.95	10636.45	17.00	320	4896	64

C. Discussions and Future Work

An analysis of results emanating from both fingerprint databases as presented in Table V and Table VI, shows that the combined feature level and Score Level fusion Gabor filter-based matching approach outperforms all the other approaches in terms of generating a good recognition performance, a reduced matching speed and a reduced memory consumption when implemented in multiple enrollment fingerprint recognition systems. A deeper analysis of the same results indicates that there is a significant percentage increase brought about by the combined feature level and Score Level fusion Gabor filter-based matching approach in comparison to the famous minutiae-based matching approach. The percentage increases in the FVC 2000-DB2-A are 86.45%, 98.01% and 87.82%, while those in the FVC 2006-DB2-A are 79.71%, 97.07% and 85.88% respectively for recognition performance improvement, matching speed improvement and memory consumption reduction. Therefore, the combined feature level and Score Level fusion Gabor filter-based matching approach significantly out competes the minutiae-based matching approach in this case.

The good performance of the combined feature Level and Score Level fusion Gabor filter-based method is attributed to a three core reasons that is: (i) during the feature level fusion, there was feature selection which was based on the good features amongst the two selected fingerprints hence generating a good final fused feature vector, (ii) there was also score level fusion performed after feature level fusion to further improve performance by taking the maximum/best scores after matching and lastly (iii) is the fact that the feature vectors generated are light making it easy to match them at a faster speed.

The features mentioned above as provided by the combined feature Level and Score Level fusion Gabor filter-based method are a good state of the art for implementation in real world applications for better recognition performance, good matching speed and reduced memory consumption.

Future work can study ways of combining feature level and score level fusion for the minutiae-based matching methods. It is anticipated that the results will surely be good basing on the experience of observations in the combined feature level and score level fusion for the Gabor filter-based matching method. There should also be further studies to deploy classification techniques such as k-Nearest Neighbor (KNN) classifier or the Support Vector Machines (SVM) classifier to further improve on the matching of the feature vectors to attain a better recognition performance, matching speed and reduce memory consumption. Future work can also look into a combined approach of using both minutiae-based methods and Gabor filter-based methods and assess the implication of deployment in multiple enrollment based fingerprint recognition systems. Such an approach may bring about a good performance but may affect memory consumption because of the many features templates to be stored. The security of the multiple templates can also be an interesting research area to venture since a lot of research has concentrated on security of single templates in single enrollment fingerprint recognition systems. Multiple enrollment can also be implemented in other biometrics such other face recognition, ear recognition, palm print recognition, and many others.

VI. CONCLUSION

This research envisioned to improve the recognition performance, running time/matching speed and reduce memory consumption in the multiple enrollment fingerprint recognition systems. A combined feature level and score level fusion Gabor filter-based multiple enrollment fingerprint recognition method has been presented and evaluated. All experiments were carried out using two public fingerprint databases, FVC 2000-DB2-A and FVC 2006-DB2-A. The experimentation results show that the combined feature level and score level fusion Gabor filter-based multiple enrollment fingerprint recognition method performs better than the minutiae-based method with significant percentage increases in recognition performance improvement, running time/matching speed improvement and memory consumption reduction. The outstanding results attained from the proposed approach leave no room for deployment in real world multiple enrollment fingerprint recognition applications that require better recognition performance, good matching speed and reduced memory consumption. This research can therefore be a basis recommendation to developers of real world multiple enrollment based fingerprint recognition systems.

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REFERENCES

[1] Fred Kaggwa, John Ngubiri and Florence Tushabe. Article: Gabor Filter-based Multiple Enrollment Fingerprint Recognition. International Journal of Computer Applications 139(7):32-38, April 2016. Published by Foundation of Computer Science (FCS), NY, USA

[2] Almudena Lindoso, Luis Entrena, Judith Liu-Jimenez, and Enrique San Millan. 2007. Correlation-based fingerprint matching with orientation field alignment. In Proceedings of the 2007 international conference on Advances in Biometrics (ICB'07), Seong-Whan Lee and Stan Z. Li (Eds.). Springer-Verlag, Berlin, Heidelberg, 713-721.

[3] Prateek Verma, Maheedhar Dubey, Praveen Verma, ”Correlation based method for identification of fingerprint- a biometricapproach,” International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249 – 8958, vol. 1, Issue 4, 2012.

[4] Bazen, Asker M., et al. "A Correlation-Based Fingerprint Verification System." (2000): 205-213.

[5] Nandakumar, Karthik, and Anil K. Jain. "Local correlation-based fingerprint matching." In Indian Conference on Computer Vision, Graphics and Image Processing. 2004.

[6] Krithika Venkataramani and B. V. K. Vijaya Kumar. 2003. Fingerprint verification using correlation filters. In Proceedings of the 4th international conference on Audio- and video-based biometric person authentication (AVBPA'03), Josef Kittler and Mark S. Nixon (Eds.). Springer-Verlag, Berlin, Heidelberg, 886-894.

[7] S. Mazumdar and V. Dhulipala, “Biometric security using fingerprint recognition,” 3, 2008.

[8] H. Patel and P. Asrodia, “Fingerprint matching using two methods,” Vol. 2, No. 3, pp. 857-860, 2012.

[9] S. Bana and D. Kaur, “Fingerprint recognition using image segmentation,” International Journal Of Advanced Engineering Sciences And Technologies, Vol. 5, pp. 012-023, 2011.

[10] Anil K. Jain, Fellow, IEEE, Salil Prabhakar, Lin Hong, and Sharath Pankanti, “Filterbank-Based Fingerprint Matching,” IEEE Transactions On Image Processing, vol. 9, No. 5, 2000.

[11] Azzoubi, Einas Almarghni, And Rosziati Bint Ibrahim. "An Enhancement Algorithm Using Gabor Filter For Fingerprint Recognition." Journal of Theoretical and Applied Information Technology 74.3 (2015).

[12] D. Maltoni, D. Maio, A.K. Jain, and S. Prabhakar, “Handbook of Fingerprint Recognition,” Springer professional computing, Springer, 2009.

[13] Ross, A. & Anil, K. Jain, (2003). Information fusion in biometrics. Pattern Recognition Letters, Vol. 24, pp. 2115–2125.

[14] E. Zhu, J. Yin, G. Zhang and C. Hu, “A Gabor filter based fingerprint enhancement scheme using average frequency", Int. Journal of Pattern Recog. and Artif. Intell., vol. 20, no. 3, pp. 417-429, 2006.

[15] Arun A. Ross, Karthik Nandakumar, and Anil K. Jain. Handbook of Multibiometrics (International Series on Biometrics). Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2006.

[16] Munir, M. U., Javed, M. Y., "Fingerprint Matching using Gabor Filters," 2005.
[17] Raymond Thai, “Fingerprint Image Enhancement and Minutiae Extraction, the School of Computer Science and Software Engineering, the University of Western Australia, 2003.
[18] S. Prabhakar, “Gabor filter bank based Fingerprint classification and identification.”, PhD. Thesis, Department of Computer Engg., MSU
[19] C. Ren, Y. Yin, J. Ma, and G. Yang, “A Novel Method of Score Level Fusion Using Multiple Impressions for Fingerprint Verification. SMC,” IEEE, pp. 5051-5056, 2009.
[20] Elmir, Youssef, et al. "Personal Identification by Fingerprints based on Gabor Filters." CIIA. 2009.
[21] Segaran, Toby. Programming Collective Intelligence: Building Smart Web 2. 0 Applications. Danbury: O'Reilly Media, Incorporated, 2007. Print.
[22] A. Ross and R. Govindarajan, "Feature Level Fusion Using Hand and Face Biometrics", Proceedings of SPIE Conference on Biometric Technology for Human Identification II, Orlando, USA, pp. 196-204, March 2005.
[23] A. Ross and R. Govindarajan, “Feature Level Fusion in Biometric Systems,” SPICE Conference on Biometric Technology for human identification.. II, Vol. 5779, Orlando USA, March 2005, pp. 196-204.
[24] A.W.K. Kong, D. Zhang, Feature-level fusion for effective palmprint authentication, in: Proceedings of the International Conference of Biometric Authentication, Hong Kong, 15–17 July 2004, pp. 761–767.
[25] A. Meraoumia, S. Citroub and A. Bouridane, “Multimodal biometrics system by fusion of palmprint and finger knuckle print using Hidden Markov Model”, IEEE. pp. 421-424, 2013.
[26] A. Meraoumia, S. Citroub and A. Bouridane, “Multimodal biometric person recognition system based on fingerprint and finger knuckle print using Correlation filter classifier”, IEEE International conference on communications, pp. 820-824, 2012.
[27] Conti V. Militello. C. Sorbello, F. & vitabile S., “A frequency based approach based approach for features fusion in fingerprint and iris multimodal biometric identification systems IEEE Transactions on Systems, Man, and Cybernetics—Part C: Applications and Reviews,Vol. 40, No. 4, pp. 384-395.
[28] Dr.S.Ravi and D.P.Mankame, “Multimodal biometric approach using fingerprint, face and enhanced iris features recognition”, International conference on circuits, power and computing technologies, pp. 1143-1150, 2013.
[29] R. Mishra, V. Pathak, “Human Recognition using fusion of Iris and Ear Data,” International Conference on Methods and Models in Computer Science, pp. 1-5, December 2009.
[30] Suryanti Awang, Rubiyah Yusof, “Fusion of Face and Signature at the Feature Level by using Correlation Pattern Recognition”, World Academy of Science, Engineering and Technology, 2011.
[31] A. Rattani, D. R. Kisku, M. Bicego, and M. Tistarelli, “Feature Level Fusion of Face and Fingerprint Biometrics,” 1st IEEE International Conference on Biometrics, Theory, Applications and Systems, pp. 1 – 6, September 2007
[32] R.Gayathri and P.Ramamoorthy “Multifeature Palmprint Recognition Using Feature Level Fusion.” International Journal of Engineering Research and Application .Vol.2,Issue 2,Mar-Apr,pp 1048 – 1054, (2012).ISSN : 2248 – 9622.
[33] R.Gayathri and P.Ramamoorthy “Palmprint recognition using feature level fusion.” J. of Comput. Sci .Vol.8, 1049-1061, 2012
[34] Norhene Gargouri and Ben Ayed. A New Human Identification Based on Fusion Fingerprints and faces biometrics using LBP and GWN descriptors, 2011 8th International Multi-conference on Systems, Signals & Devices.
[35] X. Zhou and B. Bhanu, “Feature fusion of face and Gait for Human Recognition at a distance in video”, International Conference on Pattern Recognition, Hongkong, 2006.
[36] Rattani, A., Kisku, D.R., Bicego, M., Tistarelli, M.: Robust Feature-Level Multibiometrics Classification. IEEE Biometric Consortium Conference, Biometrics Symposium, pp. 1—6 (2006)
[37] Nikhila BT, Ann J, Sabu TM. Feature Level Fusion using Multiple Fingerprints. Computational Science - New Dimensions & Perspectives . 2011:13–18,.
[38] Kisku, Dakshina Ranjan, Phalguni Gupta and Jamuna Kanta Sing. “Feature Level Fusion of Biometrics Cues: Human Identification with Doddington's Caricature.” *FGIT*(2009).
[39] A. Rattani, D. R. Kisku, M. Bicego and M. Tistarelli, "Feature Level Fusion of Face and Fingerprint Biometrics," *Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007. First IEEE International Conference on*, Crystal City, VA, 2007, pp. 1-6.
[40] Adams Kong, David Zhang, Mohamed Kamel, Palmprint identification using feature-level fusion, Pattern Recognition, Volume 39, Issue 3, March 2006, Pages 478-487, ISSN 0031-3203
[41] Poonam Mote and P.H.Zope, Multimodal Biometric system using Gabor Filter, International Journal of Advanced Trends in Computer Science and Engineering, 1 (2), May – June, 2012 , 67 - 72
[42] Gayathri, R., and P. Ramamoorthy. "Feature level fusion of palmprint and iris." IJCSI International Journal of Computer Science Issues 9.4 (2012): 194-203.
[43] Nadheen, M. Fathima, and S. Poornima. "Feature level fusion in multimodal biometric authentication system." International Journal of Computer Applications 69.18 (2013).
[44] Navdeep Bajwa, Gaurav Kumar. " Multimodal Biometric System by Feature Level Fusion of Palmprint and Fingerprint ", Volume. 4 - Issue. 07 , July - 2015, International Journal of Engineering Research & Technology (IJERT) , ISSN: 2278-0181 , www.ijert.org
[45] Kumar, N. Vinay, et al. "Features Fusion for Classification of Logos."Procedia Computer Science 85 (2016): 370-379.
[46] D. Maio, D. Maltoni, J. L.Wayman, and A. K. Jain, “Fvc2000: Fingerprint verification competition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, pp. 402-412, 2002.
[47] R. Cappelli, M. Ferrara, A. Franco and D. Maltoni, "Fingerprint verification competition 2006", Biometric Technology Today, vol.15, no.7-8, pp.7-9, August 2007.
[48] Haiyun Xu, Raymond N.J. Veldhuis, Tom A.M. Kevenaar, Anton H.M. Akkermans, and Asker M. Bazen. Spectral minutiae: A fixed-length representation of a minutiae set. Computer Vision and Pattern Recognition Workshop, 0:16, 2008.
[49] M. Haghighat, S. Zonouz, M. Abdel-Mottaleb, "CloudID: Trustworthy cloud-based and cross-enterprise biometric identification," Expert Systems with Applications, vol. 42, no. 21, pp. 7905-7916, 2015.