Analyzing State-of-the-Art Techniques for Fusion of Multimodal Biometrics

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Abstract Multimodal systems used for face recognition can be broadly classified into three categories: score level fusion, decision level fusion, and feature level fusion. In this paper, we have analyzed the performance of the three categories on various standard public databases such as Biosecure DS2, FERET, VidTIMIT, AT&T, USTB I, USTB II, RUsign, and KVKR. From our analysis, we found that score level fusion approach can effectively fuse multiple biometric modalities, and is robust to operate in less constrained conditions. In the decision fusion scheme, each decision is made after the improvement of the classifier confidence hence the recognition rate obtained is less compared to score level fusion. Feature level fusion requires less information and performs better than decision level fusion, but its recognition rate is less compared to score level fusion.

Keywords Multimodal biometrics · Score level fusion · Decision level fusion · Feature level fusion

1 Introduction

Nowadays, people demand for more secured systems and security has become a prime factor [1–14]. Unimodal systems are found to be not very efficient to recognize under uncontrolled environment. This has raised the need for more secure system using multimodal biometrics. Multimodal fusion techniques can be broadly

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classified into three categories: Score level fusion [15], decision level fusion [16], and feature level fusion [17]. Section 2 describes multimodal fusion techniques, Sect. 3 contains the Result and Discussion and Sect. 4 draws the Conclusion.

2 Multimodal Fusion Techniques

Multimodal fusion techniques are usually classified as: score level fusion [15], decision level fusion [16], and feature level fusion [17].

2.1 Score Level Fusion

Authors in [15] describe taking advantage of the uncertainty concept of the Dempster-Shafer theory; unified framework for multimodal biometric fusion is developed by improving the performance of multibiometric authentication systems. Uncertainty factors affect the recognition performance of the biometric systems. Modeling uncertainty helps to address the confidence of the fusion outcome and uncertainty of data. To improve the fusion a combination of classifier performance and quality measures is proposed to encode the uncertainty concept. Quality measures contribute unequally to recognize performance. Hence, only significant factors are fused with the Dempster-Shafer approach to generate an overall quality. In the success of uncertainty, modeling score plays an important role. In this approach multiple biometric modalities can be effectively fused, and the approach is robust to variations in classifier accuracy and quality, and enables multimodal biometric systems to operate in less constrained conditions [15]. The authors in [15] claim that their proposed approach can effectively fuse multiple biometric modalities, hence it is robust to variations in quality and classifier accuracy, and can enable multibiometric systems to operate in less constrained conditions.

2.2 Decision Level Fusion

Authors in [16] describe decision level fusion for the multimodal biometric system using social network analysis (SNA). Problems like classifier selection, dimensionality reduction, and aggregated decision making can be sought out by employing the decision fusion using SNA. Based on the similarity and correlation of features, among the classes, social networks are constructed. Fisher Linear Discriminant Analysis is used by the authors in [16] as feature extractors to reduce the dimension and to identify significant features. Based on the two levels of decision fusion methods final classification result is generated. When SNA is employed, it reduces the false acceptance rate (FAR) for both single biometric traits and multimodal biometrics. Each decision is made after the improvement of the classifier confidence in the decision fusion scheme [16]. Authors in [16] claim that the method reduces the FARs for both single and multimodal biometric traits when the SNA is employed. In case of the decision fusion scheme, each decision is made after the improvement of the classifier confidence.

2.3 Feature Level Fusion

Authors in [17] consider two biometric traits, i.e., finger-knuckle and finger-nail obtained by the single scan of dorsum hand. In this approach, a combination of finger-knuckle and finger-nail features is considered. The finger-nail biometric is considered as a unique biometric trait using Mel Frequency Cepstral Coefficient (MFCC) technique, finger-knuckle features are extracted and from second level wavelet decomposition the features of finger-nail are extracted. These features are combined using feature level fusion and classified using feedforward backpropagation neural network. Authors in [17] claim feature level fusion require less information to perform the recognition.

3 Result and Discussions

Multimodal fusion techniques: Score level fusion, decision level fusion, and feature level fusion are analyzed considering standard public databases: Biosecure DS-2 [18], FERET [19], VidTIMIT [20], AT&T [21] whose details of the databases are tabulated in Table 1 and standard public databases: USTB I [22], USTB II [22], RUSign, KVKR whose details of the databases are tabulated in Table 2.

Table 1 Details of the databases Biosecure DS-2, FERET, VidTIMIT, AT&T considered for analyses of multimodal biometrics

Properties	Biosecure DS-2 [18]	FERET [19]	VidTIMIT [20]	AT&T [21]
No. of subjects	126	1199	43	40
No. of images/videos	206	14,051	43	400
Static/Videos	Static	Static	Video	Static
Gray/Color	Four grayscale	Eight-bit grayscale	256-bit grayscale	Eight-bit grayscale
Resolution	296 * 560	256 * 384	512 * 384	92 * 112
Facial expression	Still face	Slight facial expression changes	Lip reading is done automatically	Smiling/not smiling
Illumination	Various lighting conditions	Controlled illumination	Uncontrolled illumination	N/A

Table 2 Details of the databases USTB I, USTB II, RUSign, KVKR considered for analyses of multimodal biometrics

Properties	USTB I [22]	USTB II [22]	RUsign	KVKR
No. of subjects	60	77	50	100
No. of images/videos	180	308	500	600
Static/Videos	Static	Static	Static	Static
Gray/Color	Three grayscale	Three 300 * 400 grayscale	N/A	Color
Resolution	High	High	100*100	640*480
Illumination	Various lighting condition	Various lighting condition	N/A	N/A

The recognition rate obtained by score level fusion, decision level fusion, and feature level fusion on databases: Biosecure DS-2 [18], FERET [19], VidTIMIT [20], AT&T [21], USTB I [22], USTB II [22], RUsign [23], KVKR [24] are tabulated in Table 3.

Table 3 Recognition rate obtained using score level fusion, decision level fusion, and feature level fusion

Author	Method	Database	Recognition rate	Remarks
Score Level Fusion				
Nguyen et al. [15]	Uses uncertainty concept of Dempster–Shafer theory	Biosecure DS2	100 %	This approach can effectively fuse multiple biometric modalities, and this approach is robust to operate in less constrained conditions
Decision Level Fusion				
Paul et al. [16]	Decision fusion Using SNA	FERET, VidTIMIT, AT&T, USTB I, USTB II, RUSign	92 % (Average of all the databases considered)	This approach can effectively reduce the FARs for both single and multimodal biometrics traits when SNA is employed
Feature Level Fusion				
Kale et al. [17]	Feature extraction using mel frequency cepstral coefficient technique and fusion performed using scores	KVKR	97 %	Feature level fusion and feedforward backpropagation are combined

4 Conclusion

Multimodal systems generally used for face recognition [23–30] can be broadly classified into three categories: Score level fusion, decision level fusion, and feature level fusion. In this paper, we have analyzed the performance of score level fusion, decision level fusion, and feature level fusion on various standard public databases, such as Biosecure DS-2, FERET, VidTIMIT, AT&T, USTB I, USTB II, RUsign and KVKR. From our analysis, we have found that score level fusion approach can effectively fuse multiple biometric modalities, and it is robust to operate in less constrained conditions. Furthermore, score level fusion obtains very accurate performance close to 100 % by restricting the system to accept only high-quality data. In the decision fusion scheme, each decision is made after the improvement of the classifier confidence and hence, the recognition rate obtained is less compared to score level fusion. Feature level fusion requires less information and performs better than decision level fusion, but its recognition rate is less compared to score level fusion. Thus, we conclude that score level fusion is the best fusion technique to recognize images under multimodal biometrics

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References

1. Prabhakar, S., Pankanti, S., et al.: Biometric recognition security and privacy concerns. IEEE Secur. Priv. **1**(2), 33–42 (2003)
2. Jain, A.K., Flynn, P., et al.: Handbook of Biometrics. Springer, New York (2007)
3. Down, M.P., Sands, R.J.: Biometrics: an overview of the technology, challenges and control considerations. Inf. Syst. Control J. **4**, 53–56 (2004)
4. Ross, A., Govindarajan, R.: Feature level fusion using hand and face biometrics. In: Proceedings of the SPIE 2nd Conference Biometric Technology Human Identification, Orlando, USA, pp. 196–204 (2004)
5. Chang, K., Bower, K.W., et al.: Comparison and combination of ear and face images in appearance-based biometrics. IEEE Trans. Pattern Anal. Mach. Intell. **25**(9), 1160–1165 (2003)
6. Marcialis, G.L., Roli, F.: Fingerprint verification by fusion of optical and capacitive sensors. Pattern Recognit. Lett. **25**(11), 1315–1322 (2004)
7. Ross, A., Jain, A.K.: Information fusion in biometrics. Patter Recognit. Lett. **24**(13), 2115–2125 (2003)
8. Kinnunen, T., Hautamäki, V., et al.: Fusion of spectral feature sets or accurate speaker identification. In: Proceedings of the 9th Conference Speech Computer, pp. 361–365 (2004)
9. Ross, A., Jain, A.: Information fusion in biometrics. Pattern Recogn. Lett. **24**, 2115–2125 (2003)

10. Yang, F., Ma, B.: A new mixed-mode biometrics information fusion based-on fingerprint: hand-geometry and palm-print. In: Proceedings of the IEEE Conference Image Graph, pp. 689–693 (2007)
11. Cui, J., Li, J.P., et al.: Study on multibiometric feature fusion and recognition model. In: Proceedings of the IEEE Conference Apperceiving Computing and Intelligence Analysis pp. 66–69 (2008)
12. Dahel, S.K., Xiao, Q.: Accuracy performance analysis of multimodal biometrics. Information Assurance Workshop, IEEE Systems Man and Cybernetics Society, pp. 170–173 (2003)
13. Ross, A., Nandakumar, K., et al.: Handbook of Multibiometrics. Springer, Germany (2006)
14. Ross, A., Nandakumar, K., et al.: Handbook Of Multibiometrics. Springer, USA (2011)
15. Nguyen, K., Denman, S., et al.: Score-level multibiometric fusion based on dempster–shafer theory incorporating uncertainty factor. IEEE Trans. Hum. Mach. Syst. **45**(1) (2015)
16. Paul, P.P., Gavrilova, M.L., et al.: Decision fusion for multimodal biometrics using social network analysis. IEEE Trans. Syst. Man Cybern. Syst. **44**(11) (2014)
17. Kale, K.V., Rode, Y.S., et al.: Multimodal biometric system using fingernail and finger knuckle (2013)
18. Score-level Fusion: http://personal.ee.surrey.ac.uk/Personal/Norman.Poh/web/fusionq/main.php?bodyfile=entry_page.html
19. The Facial Recogniton Technology Database: http://www.itl.nist.gov/iad/humanid/feret/feret_master.html
20. Vid TIMIT Database: http://conradsanderson.id.au/vidtimit/
21. Face Recognition: http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html
22. D Database: http://www1.ustb.edu.cn/resb/en/doc/Imagedb_123_intro_en.pdf
23. Fernandes, S.L., Josemin Bala, G.: 3D and 4D face recognition: a comprehensive review. Recent Pat. Eng. **8**(2), 112–119 (2014)
24. Fernandes, S.L., Josemin Bala, G.: Development and analysis of various state of the art techniques for face recognition under varying poses. Recent Pat. Eng. **8**(2), 143–146 (2014)
25. Fernandes, S.L., Josemin Bala, G.: Recognizing faces when images are corrupted by varying degree of noises and blurring effects. Adv. Intell. Syst. Comput. **337**(1), 101–108 (2015)
26. Fernandes, S.L., Josemin Bala, G.: Low power affordable, efficient face detection in the presence of various noises and blurring effects on a single-board computer. Adv. Intell. Syst. Comput. **337**(1), 119–127 (2015)
27. Fernandes, S.L., Josemin Bala, G.: Recognizing facial images in the presence of various noises and blurring effects using gabor wavelets, DCT neural network, hybrid spatial feature interdependence matrix. In: 2nd IEEE International Conference on Devices, Circuits and Systems (2014)
28. Fernandes, S.L., Josemin Bala, G.: Recognizing facial images using ICA, LPP, MACE gabor filters, score level fusion techniques. In: IEEE International Conference Electronics and Communication Systems (2014)
29. Fernandes, S.L., Josemin Bala, G., et al.: Robust face recognition in the presence of noises and blurring effects by fusing appearance based techniques and sparse representation. In: IEEE International Conference on Advanced Computing, Networking and Security (2013)
30. Fernandes, S.L., Josemin Bala, G., et al.: A comparative study on score level fusion techniques and MACE gabor filters for face recognition in the presence of noises and blurring effects. In: IEEE IEEE International Conference on Cloud and Ubiquitous Computing and Emerging Technologies (2013)