Multibiometrics Fusion for Identity Authentication: Dual Iris, Visible and Thermal Face Imagery

Ning Wang[1], Qiong Li[1*], Ahmed A. Abd El-Latif [1,2], Jialiang Peng[1,3] and Xiamu Niu[1]

[1]Harbin Institute of Technology, Harbin, 150080, China
[2]Menoufia University, Shebin El-Koom, 32511, Egypt
[3]Heilongjiang University, Harbin 150080, China

wangningtop@163.com, ahmed_rahiem@yahoo.com,peng80929@163.com and xiamu.niu@hit.edu.cn

Abstract

Human identification via multibiometrics is a very promising approach to improve the overall system's accuracy and recognition performance. In recent years, several approaches toward studying the fusion strategies of different biometric evidence have been proposed. However, there are a number of major problems detected on some of those approaches such as weakness against spoofing attacks and higher acceptable error rate. In this paper, a novel multibiometrics fusion strategy based on dual iris, visible and thermal face traits is proposed. Initially, the features of related biometrics (dual iris, visible with thermal faces) are fused in feature level. Then, the matching scores of iris and face traits are fused via triangular norm. The proposed multibiometrics fusion achieves higher identification performance as well as immune to spoofing attacks. All the simulation are performed based on a virtual multibiometrics database, which merges the challenging CASIA-Iris-Thousand database with noisy samples and the NVIE face database with visible and thermal face images. The results show that the proposed fusion strategy outperforms the state-of-the-art approaches in the literature.

Keywords: *Dual iris, Visible and thermal face, Feature level fusion, Score level fusion, Triangular norm*

1. Introduction

In a rapidly developing society, biometric system has the superior performance to adapt the increasing demand of accurate and efficient identity authentication 0. However, most unimodal biometric systems have several inherent disadvantages including noisy sensor data, large intra-class variations, restricted degrees of freedom, non-universality and susceptibility to spoofing attacks [2]-5]. In fact, most of the above issues can be solved via fusion multibiometrics systems, which have been widely used in some large scale authentication systems [6].

During multibiometrics fusion, the selection of biometric evidences and the fusion methodologies should be considered deliberately [7]. Considering the acceptable error rates from iris and the security from thermal face imagery, we select dual iris, visible and thermal face for fusion in our work.

Literatures on the fusion of several biometric systems are quite rich. Radu, *et al*., [8] investigate the advantages of dual iris recognition based on max and min rule. Wang, *et al*.,

[*] Corresponding author: qiong.li@hit.edu.cn

[9] fuse face and iris in feature level. They use a CFDA method to classify complex fusion vector data. Desa and Hati [10] present the face fusion recognition method in feature-level based on the infrared (IR) and visible face image. Singh et al. [11] implement score level fusion for visible and thermal face based on different face features. Nanni, *et al.*, [12] present like ratio method for combining biometric matchers in score level on Palm, Hand Geometry, Middle Finger, and Ring Finger, and the finite Gaussian mixture model is used to model the genuine and impostor score densities. Hanmandlu, *et al.*, [13] propose different triangular norms (T-norms) (Hamacher (Hm), Yager (Yg), Frank (Fk), Einstein product (Ep), *etc.*) on three biometric traits (index, middle fingers and palmprint) to confirm the effectiveness of score level fusion.

Generally, to the best of our knowledge, the fusion of left and right iris has been considered with a higher acceptance rate. The fusion of visible and thermal face can be immune to spoofing attackers. Here, we aim to elude the drawbacks of the previous works on the fusion strategy of multibiometrics in order to improve the recognition performance and enhance the robustness against spoofing attacks.

In this paper, we propose a new fusion strategy on the merged multibiometric database of dual iris, visible and thermal face imagery. Firstly, feature level fusion of left and right iris, visible and thermal face imagery are implemented separately. Then, triangular norm (T-norm) score level fusion is proposed to fuse the matching scores. The proposed fusion strategy can acquire a higher recognition performance and be immune to forgery. The comparisons suggest that the proposed approach leads to significant results than other approaches proposed in the literatures.

The remains of this paper are organized as follows. Section 2 introduces the proposed multibiometrics fusion strategy. In Section 3, the experimental results including comparisons with other approaches and analysis are presented in detail. Finally, the conclusion is drawn in Section 4.

2. Proposed Multibiometrics Fusion Strategy

2.1. The main architecture of the proposed fusion strategy

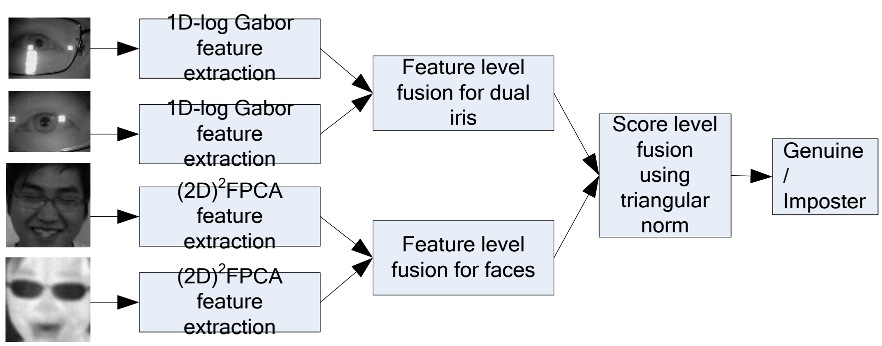
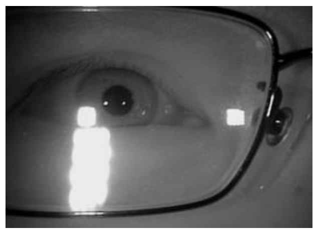


Figure 1. The architecture of the proposed multibiometrics fusion strategy

Herein, we introduce a novel multibiometrics fusion strategy. The architecture of the proposed approach is depicted in Figure 1. The feature sets of dual iris are homogeneous, and so as visible and thermal feature sets. Feature level fusion refers to combining different feature sets, and a single resultant feature vector can be calculated. In the proposed fusion strategy, left and right iris features are extracted based on 1D-log Gabor algorithm [14]. Visible and thermal face features are extracted via (2D)^{2}FPCA algorithm [15]. These features are fused at the feature level to get the matching score separately. Then, the scores of iris and face are fused through T-norm to acquire a closer genuine and larger imposter score. The detail of every step of this strategy is described in the following sub-sections.

2.2. Preprocessing and feature extraction

The iris sample in CASIA-Iris-Thousand iris database [16] is shown in Figure 2(a). Some noises including reflection spots, glass frame, and eyelash affect the iris localization performance, and then affect the iris feature extraction for recognition.



(a) Noisy iris sample

(b) Thermal face sample

Figure 2. The samples from iris and face database

In our work, we first use Navier-Stokes (NS) equation which was proposed by Bertalmio, *et al.*, [17] for reflection removal. It produces a revised iris image, which the reflection region is seamlessly merged into a reign in a way that is not detectable by the edge detection operator. After reflection removal, we introduce the Probable boundary (Pb) edge operator, which was firstly proposed by Martin, *et al.*, [18], into pupil edge detection process. The Pb operator provides a more principled approach by framing the task as a supervised learning problem and it searches local discontinuities in several feature channels over a range of orientations and scales [19].

After iris and pupil localization, the iris ring is normalized to a rectangular with polar coordinate transformation. The histogram equalization operation is implemented on this iris ring. Afterwards, the 1D Log-Gabor filter shown in Eq. (1) is used to extract the iris binary feature vector.

$$G(\omega) = \exp\left(\frac{-\left(\log\left(\frac{\omega}{\omega_0}\right)\right)^2}{2\left(\log\left(\frac{\sigma}{\omega_0}\right)\right)^2} \right) \tag{1}$$

where ω_0 represents the center frequency, and σ gives the bandwidth of the filter. In our work, $\omega_0 = 1/18$ and $\sigma = 1/36$.

Figure 2(b) shows the thermal face image sample from Natural Visible and Infrared facial Expression (NVIE) face database [20]. Visible face can be located via adaboost algorithm [21]. If the thermal face image has its visible face image correspondingly, we can utilize the location of visible face directly to locate thermal face. If hasn't, according to the property of gray thermal image, we select the adaptive threshold using OTSU method [22] to get binary and the Canny edge. Then fit the ellipse expressed in Eq. (2) for face edge using Hough transform.

$$\frac{\left((x-p)\cos\theta+(y-q)\sin\theta\right)^2}{a^2}+\frac{\left(-(x-p)\sin\theta+(y-q)\cos\theta\right)^2}{b^2}=1 \tag{2}$$

After face location, the glasses in thermal face are filled with the mean gray value of the other face part. The face parts of visible and thermal are normalized into the size of 80×80. The $(2D)^2$FPCA [15] algorithm is implemented for feature extraction. This $(2D)^2$-based method essentially works in the row direction using PCA and column direction using LDA with fewer number of coefficients for efficient representation. It is easier to evaluate the image covariance matrix accurately to resist the small sample size problem. The process of $(2D)^2$FPCA is shown in Figure 3. The visible and thermal face feature vectors with real numbers are acquired after the above procedures.

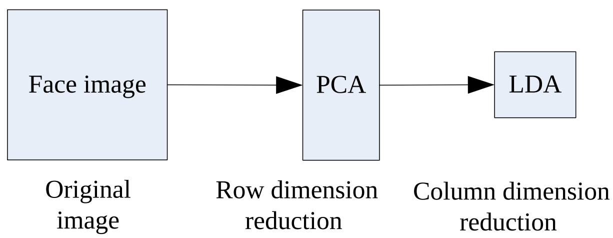


Figure 3. The process of $(2D)^2$FPCA feature extraction

2.3. Feature level fusion for the related biometrics

Feature level fusion can keep the discrimination of different biometric modal as much as possible. In our work, we introduce the complex fusion [9] for dual iris, visible and thermal faces.

Suppose $\alpha=[\alpha_1\cdots\alpha_{d_1}]^T$ and $\beta=[\beta_1\cdots\beta_{d_2}]^T$ are two feature vectors. Our feature level fusion strategy is expressed as:

$$F=\begin{cases}(\alpha_1+i\beta_1,\cdots,\alpha_{d_2}+i\beta_{d_2},\alpha_{d_2+1}+i0,\cdots,\alpha_{d_1}+i0), if\ d_1\ge d_2\\(\alpha_1+i\beta_1,\cdots,\alpha_{d_1}+i\beta_{d_1},0+i\beta_{d_1+1},\cdots,0+i\beta_{d_2}),\ if\ d_1<d_2\end{cases} \tag{3}$$

For dual iris fusion, suppose I_L and I_R are the left and right iris binary feature vectors. The complex fusion vector can be expressed in Eq. (4) :

$$F_{Ii}=I_{Li}+i\times I_{Ri},\ \ i\in N \tag{4}$$

The distance S_{F_I} of the two complex iris fusion vectors F_{I1} and F_{I2} is acquired via Eqs. (5), (6) and (7):

$$S_{F_I}=\|HDF\|_2 \tag{5}$$

$$HDF=(HD(I_{L1},I_{L2}),\ HD(I_{R1},I_{R2})) \tag{6}$$

$$HD(A,B)=\frac{\|Code_A\otimes Code_B\cap Mask_A\cap Mask_B\|}{Mask_A\cap Mask_B} \tag{7}$$

where HD stands for the Hamming distance, $Mask_A$ and $Mask_B$ are the masks of reflection region and eyelash in iris image, $Code_A$ and $Code_B$ are the iris feature vectors.

For face fusion, suppose F_V and F_T stands for the real number feature vectors of visible and thermal face imageries. The complex fusion vector can be expressed in Eq. (8):

$$F_{Fi} = F_{Vi} + i \times F_{Ti}, \quad i \in N \tag{8}$$

The distance of two complex face fusion vectors F_{F1} and F_{F2} is computed via Eq. (9):

$$S_{F_F} = \|F_{F1}\text{-}F_{F2}\| = \sqrt{(F_{F1}\text{-}F_{F2})^{\mathrm{H}}(F_{F1}\text{-}F_{F2})} \tag{9}$$

2.4. Score level fusion using triangular norm

After obtaining the feature level fusion scores of iris and face biometric systems, the score level fusion is applied. Hanmandlu *et al.*, have proposed T-norms for score level fusion on the hand part in [13]. T-norm has up a convex function graph, and this can make closer genuine and higher imposter fusion distance scores. We apply T-norms to fuse scores S_1 and S_2 in score level, which are as follows:

1) Hamacher: $\dfrac{S_1 S_2}{S_1 + S_2 - S_1 S_2}$
2) Yager: $\max\left(1-\left(\left(1-S_1\right)^p+\left(1-S_2\right)^p\right)^{1/p},0\right), p>0$
3) Frank: $\log_p\left(1+\dfrac{(p^{S_1}-1)(p^{S_2}-1)}{p-1}\right), p>0$
4) Einstein product: $\dfrac{S_1 S_2}{2-\left(S_1+S_2-S_1 S_2\right)}$

Before using T-norm, the matching data should be normalized by Eq. (10):

$$S = \frac{S - \min(S)}{\max(S) - \min(S)} \tag{10}$$

3. Experimental Results and Analysis

3.1. Experiments setup and evaluation protocols

The proposed fusion strategy is tested on the merged virtual multibiometric database, which contains dual iris, visible and thermal face imagery. The iris sub-database named CASIA-Iris-Thousand [16] is a challenging database which includes many noisy iris images. The face sub-database NVIE database contains visible and infrared thermal face imagery with six different expressions [20]. In our work, we randomly select 90 classes with every 10 samples to test the proposed approach.

False Matching Rate (FMR) and False Non-Matching Rate (FNMR) are preferred to evaluate the performance of the algorithms in an off-line technology test [23]. Evaluation protocol Equal Error Rate (EER, when FMR = FNMR)) and Receiver Operator Characteristic (ROC) curve which is the plot of FMR (t) against 1-FNMR (t) for various decision thresholds are carried out for the recognition performance.

Another evaluation criterion is the Weighted Error Rate (WER) [24] defined as Eq. (11):

$$WER(\alpha, th) = \alpha FMR + (1-\alpha) FNMR \tag{11}$$

Where $\alpha \in [0,1]$ is the balancing factor and th is the threshold. The optimal threshold that minimizes WER can be calculated as Eq. (12):

$$th_{\alpha}^{*} = \arg\min_{th} WER(\alpha, th) \tag{12}$$

Finally, the Half Total Error Rate (HTER) indicator can be defined as Eq. (13):

$$HTER(th_{\alpha}^{*}) = \frac{FMR(th_{\alpha}^{*}) + FNMR(th_{\alpha}^{*})}{2} \tag{13}$$

The Expected Performance Curves (EPC) [25] can be interpreted in the same manner as the ROC curve, *i.e.*, the lower the value of HTER in the EPC, the better the performance for the given cost is (controlled by α). It makes the biometric system more flexible, robust and secure.

Suppose the score distribution of imposer and genuine belongs to normal distribution [23]. The parameter d' can be used to compute the difference between two normal distributions as follows:

$$d' = \frac{|\mu_1 - \mu_2|}{\sqrt{(\sigma_1 + \sigma_2)/2}} \tag{14}$$

where μ_1 and σ_1 are the mean and variance of genuine score distribution N_1, and μ_2 and σ_2 are the mean and variance of the imposter matching result distribution N_2. The higher d' value, the better accuracy will be.

3.2. Comparisons and analysis

The recognition performance of different biometric systems via the EER, HTER, and d’ criteria are shown in Table 1. Some insights gleaned from this table are as follows. The performances of unimodal biometric systems of visible (V) and thermal (T) face are the lowest. The performance of the two biometrics fusion strategies of VT_F in feature level and VT_sum at score level are better than unimodal systems V and T.

From biometric strategies of No.5 to No.10, we can see that iris biometrics play better recognition performance than faces systems No.1 to No.4. Left iris (L) shows better performance than right iris (R). This is because of the noise in the iris acquiring process. Fusion of the dual iris (No.7, 9, 10 and 11) gives better performance than unimodal iris.

LR_Sum shows better performance than the other two strategies of LR_Max and LR_Min. These phenomena can also be seen in Figure 4.

Table 1. The recognition performance of different biometric strategies

No.	Strategy	EER%	HTER%	d’
1	Thermal face (T)	10.70	10.30	2.39
2	Visible face (V)	6.71	6.07	3.02
3	VT feature level (VT_F) [19]	3.94	3.69	3.34
4	VT Score Sum (VT_Sum) [20]	3.70	3.49	3.40
5	Right iris (R)	2.31	1.99	3.46
6	Left iris (L)	2.11	1.41	3.74
7	LR Score Max (LR_Max) [16]	1.70	1.42	3.57
8	Proposed LRVT Hm	1.69	1.65	3.90
9	LR Score Min (LR_Min) [16]	1.15	0.99	4.28
10	LR Score Sum (LR_Sum)	0.94	0.58	4.22
11	LR feature level (LR_F)	0.93	0.58	4.21
12	Proposed LRVT Fk (p=0. 5)	0.47	0.39	4.38
13	Proposed LRVT Ep	0.46	0.32	4.36
14	Proposed LRVT Sum	0.23	0.13	5.39
15	Proposed LRVT Yg (p=2)	0.09	0.04	5.71

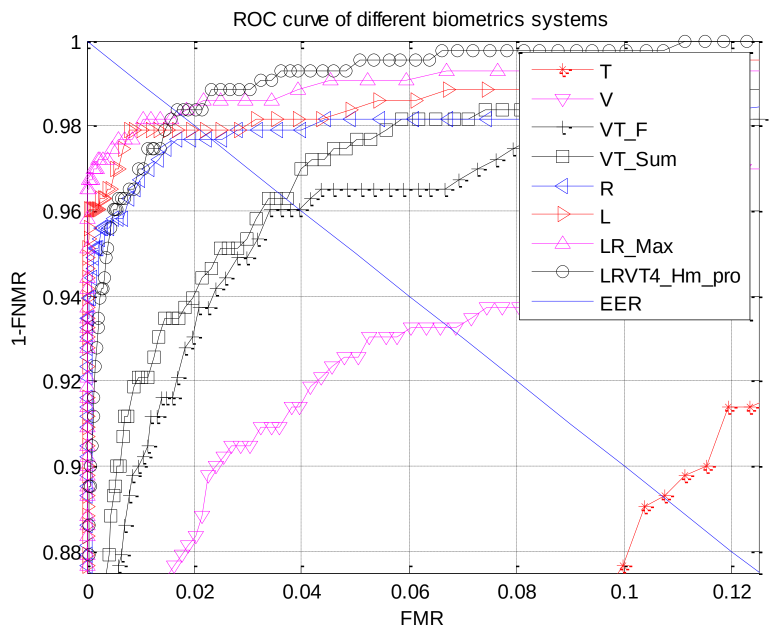


Figure 4. The ROC curve of lower performance biometrics systems

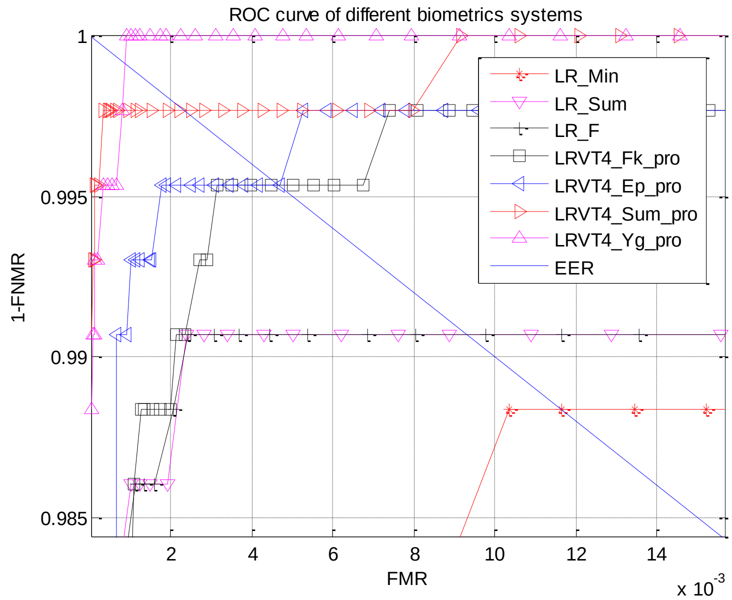


Figure 5. The ROC curve of higher performance biometrics systems

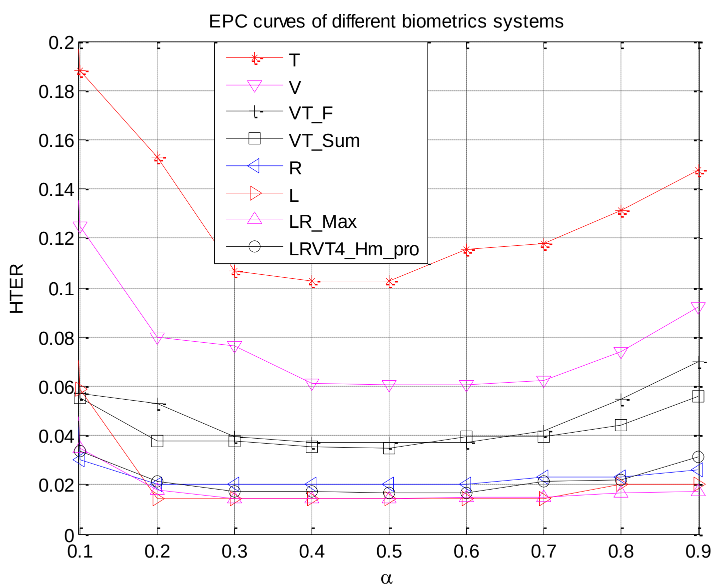


Figure 6. The EPC curve of lower performance biometrics systems

From Table 1 and Figure 5, we find out that our proposed fusion strategies show very good performance in the LRVT4_Hm system. Sum rule can give a good performance. From this comparison, proposed fusion strategies (No.12, 13, 14 and 15) obviously enlarge the discrimination of genuine and imposter scores to get the acceptable EER. The best one of them is the proposed LRVT_Yg fusion strategy, it can achieve the EER of 0.09 when p=2.

From Table 1, we can also see that in the evaluation of HTER and d', the performance of the comparison fusion strategies show the same situation as EER. To better compare the recognition performance, we divide all the systems into two main sets: lower and higher performance sets. From Figure 4 and Figure 5 give the ROC curves of all the comparison and proposed biometrics systems. We get the best recognition performance in the strategy of LRVT4_Yg.

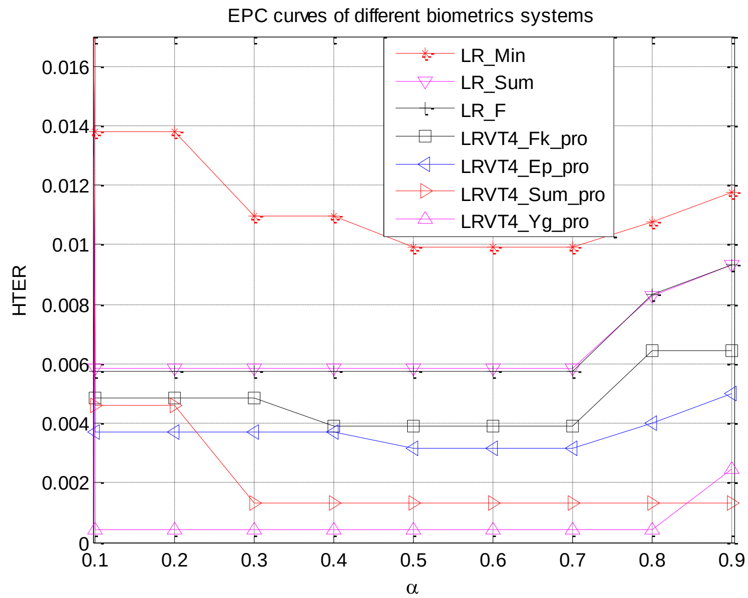


Figure 7. The EPC curves of higher performance biometrics systems

The EPC curves of all the systems are shown in Figure 6 and Figure 7. From Figure 6, α could be selected in the value of 0.4 and 0.5 to get best recognition performance. From Figure 7, α could be selected in the value of 0.5, 0.6 and 0.7.

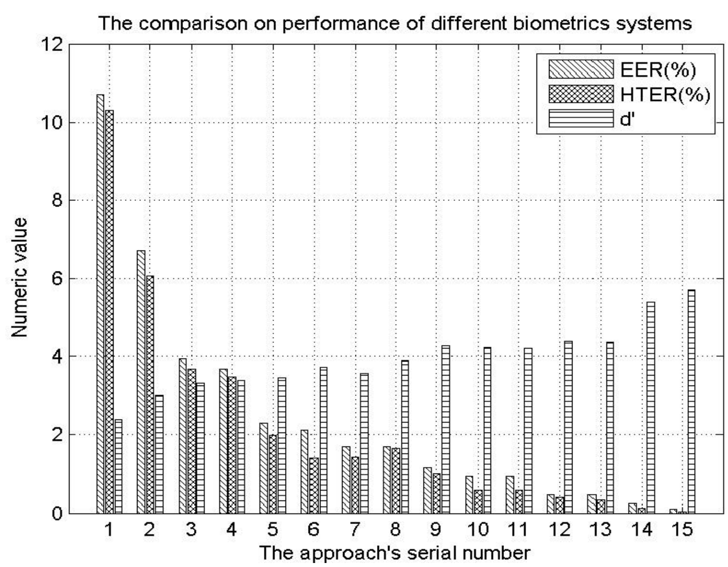


Figure 8. The comparison of performance of different biometric systems

We give the bar graph performance comparison for different evaluation protocols as shown in Figure 8. We can see that the proposed fusion strategy LRVT4_Yg when p=2 gives an excellent recognition performance from different evaluation protocols.

4. Conclusion

For multibiometric systems, the effective fusion strategy is necessary for combining information from several single biometric systems. In this paper, an efficient multibiometrics fusion approach that fuses dual iris, visible and thermal face imageries is proposed. It has better recognition performance and can defense the forgery attacks. We have performed several experimental tests and analysis based on a virtual multibiometric database. The insights gleaned from the tests suggest that the proposed fusion approach has superior performance to other approaches proposed in the literatures.

Acknowledgements

This work is supported by the Fundamental Research Funds for the Central Universities (Grant Number: HIT. NSRIF. 2013061).

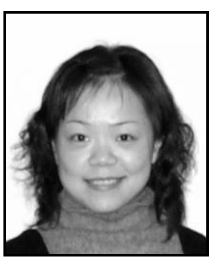
References

[1] A. K. Jain, P. Flynn and A. Ross, Handbook of Biometrics, chap. Introduction to Biometrics, Springer, NJ, USA, **(2008)**, pp. 11-22.
[2] J. Feng and A. K. Jain, “Fingerprint Reconstruction: From Minutiae to Phase”, IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 2, **(2011)**, pp. 209-223.
[3] J. Galbally, J. Fierrez, J. Ortega-Garcia, C. McCool and S. Marcel, “Hill-climbing attack to an Eigenface-based face verification system”, Proceedings of the 1st IEEE International Conference on Biometrics, Identity and Security, Tampa, FL, United states, **(2009)** September 22-23, pp. 1-6.
[4] G. Wang and H. Wu, “Research and Realization on Voice Restoration Technique for Voice Communication Software”, Proceedings of 2009 International Symposium on Information Engineering and Electronic Commerce, Ternopil, Ukraine, **(2009)** May 16-17, pp. 791-795.
[5] S. Venugopalan and M. Savvides, “How to Generate Spoofed Irises From an Iris Code Template”, IEEE Trans. Inf. Foren. Sec., vol. 6, no. 2, **(2011)**, pp. 385-395.
[6] A. Nagar, K. Nandakumar and A. K. Jain, “Multibiometric Cryptosystems Based on Feature-Level Fusion”, IEEE Trans. Inf. Foren. Sec., vol. 7, no, 1, **(2012)**, pp. 255-268.
[7] A. A. Ross, K. Nandakumar and A. K. Jain, “Handbook of Multibiometrics, Springer, London, 1nd edn., **(2006)**.
[8] P. Radu, K. Sirlantzis, G. Howells, S. Hoque and F. Deravi, “Are Two Eyes Better than One?”, An Experimental Investigation on Dual Iris Recognition. Proceedings of **2010** International Conference on Emerging Security Technologies, Canterbury, United kingdom, **(2010)** September 6-8, pp. 7-12.
[9] Z. Wang, Q. Han, X. Niu and C. Busch, “Feature-Level Fusion of Iris and Face for Personal Identification”, Lect. Notes Comput. Sci., vol. 5553, **(2009)**, pp. 356-364.
[10] M. Shahbe and S. Hati, “Ir And Visible Face Recognition Using Fusion of Kernel Based Features”, Proceedings of the 19th International Conference on Pattern Recognition, Tampa, FL, United states, **(2008)** December 8-11, pp. 1-4.
[11] R. Singh, M. Vatsa and A. Noore, “Integrated Multilevel Image Fusion and Match Score Fusion of Visible and Infrared Face Images for Robust Face Recognition”, Pattern. Recogn., vol. 41, no. 2, **(2008)**, pp. 880-893.
[12] L. Nanni, A. Lumini and S. Brahnam, “Likelihood Ratio Based Features for A Trained Biometric Score Fusion”, Expert Systems with Applications, vol. 38, no. 1, **(2011)**, pp. 58-63.
[13] M. Hanmandlu, J. Grover, A. Gureja and H. Gupta, “Score Level Fusion of Multimodal Biometrics Using Triangular Norms, Pattern Recogn. Lett., vol. 32, no. 1, **(2011)**, pp. 1843-1850.
[14] N. Wang, Q. Li, A. A. A. El-Latif, T. Zhang and X. Niu, “Toward Accurate Localization and High Recognition Performance for Noisy Iris Images (DOI:10.1007/s11042-012-1278-7), Multimed. Tools Appl..
[15] N. Wang, Q. Li, A. A. A. El-Latif, J. Peng and X. Niu, “$(2D)^2$MFPCA: An Efficient Approach for Thermal Face Recognition”, To be appear.

[16] H. Li, Z. Sun and T. Tan, "Robust Iris Segmentation Based on Learned Boundary Detectors", Proceedings of the 5th IAPR International Conference on Biometrics, New Delhi, India, **(2012)** March 29-April 1, pp. 317-322.
[17] M. Bertalmio, A. L. Bertozzi and G. Sapiro, Navier-Stokes, "Fluid Dynamics and Image And Video Inpainting", Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Kauai, HI, United states, **(2001)** December 8-14, pp. 355-362.
[18] D. Martin, C. Fowlkes and J. Malik, "Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues", IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 5, **(2004)**, pp. 530-549.
[19] N. Wang, Q. Li, A. A. A. El-Latif, T. Zhang and J. Peng, "An accurate iris location method for low quality iris images", Proceedings of the 4th International Conference on Digital Image Processing, Proceedings of the SPIE, vol. 8334, **(2012)**, pp. 833411(1-4).
[20] S. Wang, Z. Liu, S. Lv, Y. Lv, G. Wu, P. Peng, F. Chen and X. Wang, "A Natural Visible and Infrared Facial Expression Database for Expression Recognition and Emotion Inference", IEEE Trans. on Multimedia, vol. 12, no. 7, **(2010)**, pp. 682-691.
[21] Y. Freund and R. E. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting", J. Comput. Syst., vol. 55, **(1997)**, pp. 119-139.
[22] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Trans. Syst. Man. Cyc., vol. 9, no. 1, **(1979)**, pp. 62-66.
[23] J. Daugman, "Biometric Decision Landscapes", Cambridge University Computer Laboratory, Technical Report, **(2000)**, no. 482.
[24] S. Bengio and J. Mariéthoz, "A Statistical Significance Test for Person Authentication", The Speaker and Language Recognition Workshop, Toledo, Spain, **(2004)** May 31-June 3, pp. 237-244.
[25] S. Bengio and J. Mariéthoz, "The Expected Performance Curve: A New Assessment Measure for Person Authentication", The Speaker and Language Recognition Workshop, Toledo, Spain, **(2004)** May 31-June 3, pp. 279-284.

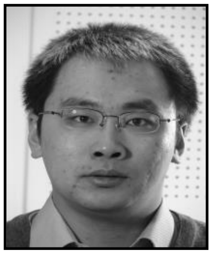
Authors

Ning Wang was born in China, in November 1984. He received the B. S degree and M. S. degree in Mathematics in Harbin Institute of Technology (HIT), Harbin, P. R. China in 2006 and 2008, respectively. Now, he is a Ph.D student in the School of Computer Science and Technology, Harbin Institute of Technology. His research interests include iris recognition, face recognition, multi-biometrics recognition, template protection and information theory. E-mail: wangningtop@163.com.



Qiong Li was born in China. She received her B.S., M.S. and Ph.D degree from Harbin Institute of Technology, in 1997, 1999 and 2005, respectively. She is now working at Harbin Institute of Technology as an assistant professor. Her research interests include biometric recognition, information security, multimedia security and quantum information security. E-mail: qiongli@hit.edu.cn.

Ahmed A. Abd El-Latif was born in Egypt, in July 1984. He received the B.S. degree with honor rank in Mathematics and Computer Science from Menoufia University, Egypt in 2005, and M.S. degree in Computer Science in 2010. He was a teaching assistant in Mathematics department from March 2007 to May 2010. He is currently pursuing the Ph.D. degree at Harbin Institute of Technology (H.I.T), Harbin, P. R. China. He is a referee of many referred international journals and conferences. His areas of interests are cryptography, image segmentation, application of chaotic systems in multimedia content encryption, biometrics encryption, secret image sharing and biometrics. E-mail: ahmed_rahiem@yahoo.com.



Jialiang Peng was born in China, in November 1980. He received the B.S degree and M.S. degree in Computer Science in Heilong Jiang University, Harbin, P. R. China in 2002 and 2005, respectively. Now, he is a Ph.D student in the School of Computer Science and Technology, Harbin Institute of Technology. His research interests include vein recognition, fingerprint recognition, multi-biometrics recognition, template protection and information theory. E-mail: peng80929@163.com.

Xiamu Niu was born in China, in May 1961, received the B.S. degree and M.S. degree in Communication and Electronic Engineering from Harbin Institute of Technology (HIT), Harbin, P. R. China in 1982 and 1989 respectively, and received the Ph.D degree in Instrument Science and Technology in 2000. He was an invited scientist and staff member in Department of Security Technology for Graphics and Communication System, Fruanhofer Institute for Computer Graphics, Germany, from 2000 to 2002. He was awarded the Excellent Ph.D Dissertation of China in 2002. He now is the Professor (doctoral advisor) and Superintendent of Information Countermeasure Technique Institute HIT, Director of Information Security Technique Research Center, HIT-ShenZhen. He is SPIE member, ACM member, IEEE member, and the advanced CIE member. He has published 3 works and more than 140 papers cited by SCI and EI. His current research fields include computer information security, hiding communication, cryptography, digital watermarking, signal processing and image processing etc. E-mail: xiamu.niu@hit.edu.cn.