An Enhanced Algorithm for Thermal Face Recognition

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@ict.hit.edu.cn

Abstract

In this paper, an enhanced thermal face recognition method, namely GMFB, is proposed. Initially, Gabor Jet Descriptor (GJD) is extracted from each thermal image with five scales and eight orientations. Then, the Modified Fisher (MF) criterion is implemented on the feature vector for every scale. Finally, the Borda count (BC) matching method is used to get higher matching score. Our proposed method enhances the discrimination ability of the feature vector significantly. Experiments conducted on NVIE thermal face database show that the proposed approach outperforms the state-of-the-art methods.

Keywords: *Thermal face recognition; Gabor Jet Descriptor; Modified Fisher; Borda Count*

1. Introduction

Many biometric patterns have been used for identity verification nowadays, such as face, fingerprint, iris, vein, palm-print and so on [1]. Although perhaps the most natural way for personal identification, the visible spectrum faces recognition is still a highly challenging task. It has suffered from different variations such as dim lighting, non-uniform illumination, viewing directions, poses and ethnic groups [2]. Furthermore, it is still possible for the attackers to get the biometric template and reconstruct the pattern to spoof different verification application systems, even though the template protection technique is applied [3, 4].

However, recent years has witnessed the growing interest for verification using different biometric modalities, particularly thermal Infra-Red (IR) face image [5, 6]. Thermal IR sensor measures the heat energy, which belongs to long-wave IR (8-12μm) spectrum band emitted. It is not reflected, but obtained from the objects themselves and is unique to each individual [7]. This thermal technique is less subject to scattering and absorption by smoke or dust than visible light, and even works well in complete darkness. It can minimize the effect of illumination changes and occlusion generated by moustache, beards, facial hair, hairstyle etc. More importantly, the thermal image is immune to fake samples due to that the heat energy can only be captured from a live individual [8, 9].

Most of the developed methods for thermal face recognition are based on the appearance. For instance, Principal Component Analysis (PCA) [10], Linear Discriminant Analysis (LDA) [10], Kernel Principal Component Analysis (KPCA) [11], Scale Invariant Features

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

Transform (SIFT) [12], Local Binary Pattern (LBP) [13], Speed Up Robust Features (SURF) [5], *etc*. Dimension reduction based algorithms (PCA, KPCA, LDA) transform the image into a 1D vector to get a projective vector in a high dimensional image space, and it is difficult to evaluate the covariance matrix accurately because of small sample size problems [15]. As a global matching method, SIFT extracts local interest points independently as the local descriptors, while SURF algorithm computes local interest points and descriptors at a higher speed and a lower number of components than SIFT. Another local matching method, LBP considers the local gradient histogram for efficient texture information representation and concatenates the regional features to get the global description of the thermal face. However, thermal images have less interest points and less gradient due to temperature map, so it is hard to achieve an excellent recognition performance using local and global matching approaches.

Previous studies demonstrate that Gabor Jet Descriptor (GJD)-based methods are extremely useful for visible face recognition in terms of some interference factors. Lades *et al.*, [16] pioneered the implementation of Gabor wavelets for face recognition via the Dynamic Link Architecture (DLA) framework. Wiskott *et al.*, [17] further expand DLA and develop Gabor wavelet based elastic bunch graph matching approach to label and recognize human faces. These methods are developed initially for visible face recognition, and the drawback is that the face key parts need to be marked manually. Liu and Wechsler [18] concatenate the 40 Gabor wavelet representations (Gabor filters of five scales and eight orientations are used) of one sample image as a feature vector. To avoid the high dimension space problem, the down-sampling operation using Linear Discrimination Analysis (LDA) and Principle Component Analysis (PCA) are implemented. Zou *et al.*, [19] divide the concatenated feature into 5 parts according to the scale and regards each part as a GJD, and then uses BC matching method to acquire a higher matching score. Hermosilla *et al.*, [14] applies this approach into thermal face recognition. It is noted that the study in [19] obtains the lower dimension feature vector and achieves a better performance. However, this GJD-BC method hasn’t considered the discrimination of every scale representation with eight orientations. During the research, we find out that the features in the same scale have the same property of discrimination.

In this paper, we propose a new approach for thermal face recognition, namely GMFB, based on Gabor Jet Descriptor, Modified Fisher and Borda Count matching method. The proposed approach adopts Gabor Jet Descriptor to extract the Gabor feature representations in 5 scales and 8 orientations. Then, the Modified Fisher criterion [20] is introduced in order to reduce the dimension of features belonging to the same scale. Finally, the Borda Count matching method is used to get a higher matching score using these 5 sacles matching results. The experimental results show that the proposed method effectively enhances the discrimination ability of the feature vector.

The rest of this paper is organized as follows. In Section 2, the proposed algorithm is described in detail. Section 3 is devoted to the experimental results and analysis. Finally, Section 4 concludes this paper.

2. Proposed GMFB Recognition approach for Thermal face Image

This section describes our implementation of the proposed thermal face recognition approach, namely GMFB. Figure 1 shows its schematic diagram. In enrollment phase, thermal face images are preprocessed firstly, and it contains face calibrating and localization. Secondly, Gabor wavelets with five scales and eight directions are used to extract the thermal face texture features. These Gabor representations are divided into 5 GJDs based on their scales, and every GJD has the features with eight orientations. Then, for every GJD, we train the enrollment samples to get the projective vector by Modified Fisher Discrimination algorithm and store these projective and dimension reduced vectors into a template database. While in the authentication phase, the projective vectors are taken out for the authentication samples to extract lower dimension feature vectors. Finally, BC matching is implemented to obtain a higher matching score and a better recognition performance. The details of every procedure of the proposed GMFB thermal face recognition approach are as follows.

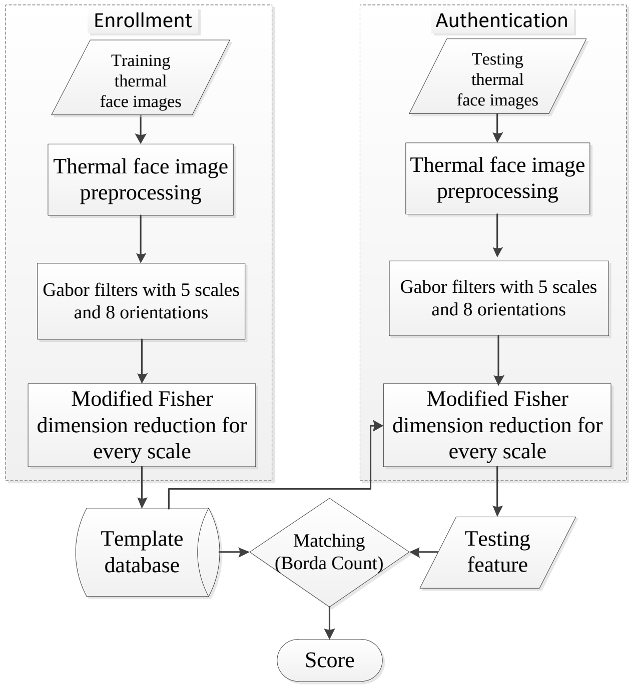

Figure 1. The Schematic Diagram of the Proposed Approach

2.1. Thermal Face Image Preprocessing

It is easier to preprocess thermal face image than visible face image. There are two situations. If the thermal face image has its corresponding visible face image, it means the visible camera and thermal sensors and in the same location exactly. We can take the region of visible face as thermal face region directly using some popular localization algorithm [21]. Otherwise, if the two sensors are not in the same location, it needs to develop some thermal face localization methods specially. According to the property of gray level thermal image, we select the adaptive threshold via OTSU algorithm [22] for binary, and then fit the ellipse using Hough transforms parameters based on Canny edge [23]. Finally, the thermal face is calibrated through long axis of ellipse, and the glass regions are localized through adaptive threshold and filled by the average value of the rest thermal face part [24].

2.2. Extracting GJD Features and Dimension Reduction for every Scale

Daugman pioneers 1D Gabor filters to the 2D Gabor filters [25], which play a significant role in texture representation. While the Gabor wavelets, whose kernels as shown in Eq. (1), are similar to the 2D receptive field profiles of the mammalian cortical simple cells. They exhibit desirable characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains.

$$\psi_{\mu,\nu}(z) = \frac{\| k_{\mu,\nu} \|^2}{\sigma^2} e^{(-\|k_{\mu,\nu}\|^2 \|z\|^2 / 2\sigma^2)} [e^{ik_{\mu,\nu} z} - e^{-\sigma^2/2}] \tag{1}$$

where μ and ν define the orientation and scale of the Gabor kernels, $z = (x, y)$ denotes the pixel in image and $\|\cdot\|$ stands for the norm operator. The wave vector $k_{\mu,\nu}$ is expressed as Eq. (2):

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu} \tag{2}$$

where $k_\nu = k_{max} / f^\nu$ is the sampling frequency for the filter. The parameter $k_{\max}$ is the maximum sampling frequency, and f is the spacing factor between kernels in the frequency domain [16]. The parameter $\phi_\mu = \pi\mu / 8$ shows the direction selection of filters, and σ determines the ratio of Gaussian window width with wavelength and its relationship with the bandwidth of the filter is:

$$\sigma = \sqrt{2ln2\left(\frac{2^\omega + 1}{2^\omega - 1}\right)} \tag{3}$$

where ω denotes a half-magnitude bandwidth.

Let $I(z)$ be the gray level distribution of an image, the convolution of image I and a Gabor kernel $\phi_{\mu,\nu}$ are defined via Eq. (4):

$$O_{\mu,\nu}(Z) = I(z) * \psi(z_0) = \int I(z) \psi_{\mu,\nu}(z_0 - z) d^2 z \tag{4}$$

where $z = (x, y)$, $*$ denotes the convolution operator, and $O_{\mu,\nu}(z)$ is the convolution result constituting with real and imaginary parts.

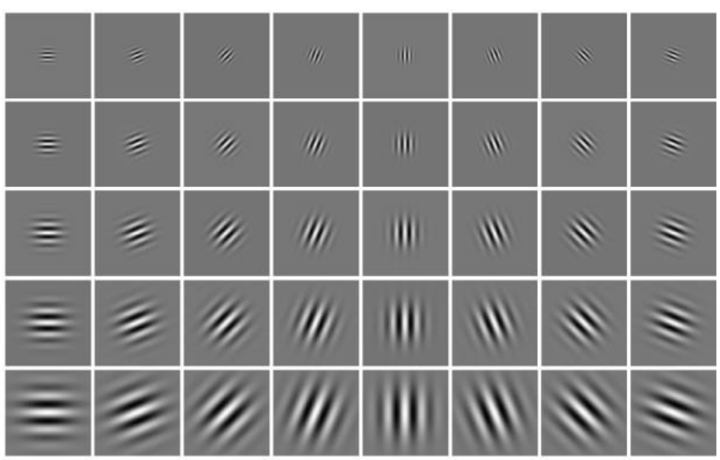

Figure 2. The Real Part of the Gabor Kernels in 5 Scales and 8 Orientations

The real and imaginary parts of the convolution oscillate easily, and the phase has rotation usually. These factors affect the recognition performance. In our work, we select the amplitude as the Gabor wavelet representation feature which is relatively stable and will reflect the energy spectrum of the thermal face image. To better interpret the Gabor kernel's characteristics of spatial frequency, spatial locality, and orientation selectivity, Figure 2 gives the real part of the Gabor kernels at 5 scales and 8 orientations, and the magnitude parts after convolution with thermal face image as shown in Figure 3.

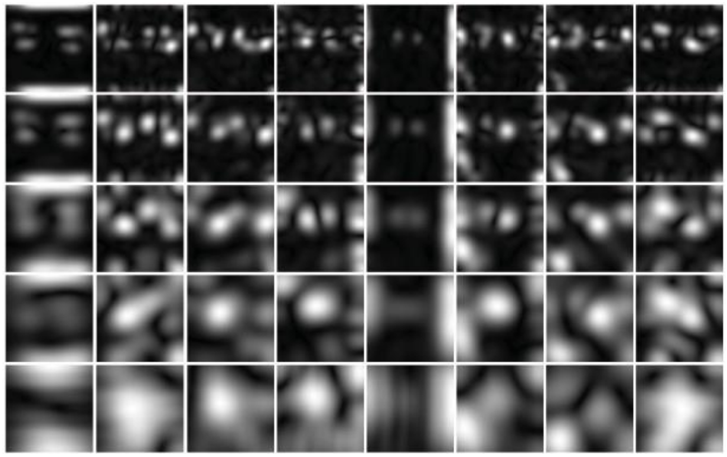

Figure 3. The Magnitude of Convolution in 5 Scales and 8 Orientations

In our study, for Gabor wavelets, $\nu \in \{0,...,4\}$, $\mu \in \{0,...,7\}$, and with the following parameters: $\sigma = 2\pi$, $k_{max} = \pi / 2$ and $f = \sqrt{2}$. Gabor wavelet representation results generate 40 times of the original thermal face image size. For an thermal image with size of $M \times N$, we divide the magnitude representation into L small sub-images. Here, $L = m \times n$, and the size of every sub-image is $s_m \times s_n$, where $m = M / s_m$ and $n = N / s_n$. So, the mean gray value of every sub-image is:

$$u_k = \frac{\sum_{(x,y) \in I_k} M_k(x,y)}{s_m \times s_n} \tag{5}$$

where

$$M_k(x,y) = \sqrt{(Re(O_k(x,y)))^2 + (Im(O_k(x,y)))^2} \tag{6}$$

$Re(O_k(x,y))$ and $Im(O_k(x,y))$ are the real part and imaginary part of $O_k(x,y)$. In our experiments, the parameters are $M = 80$, $N = 80$, $s_m = 16$, $s_n = 16$ and $L = 25$.

After that, we put these mean gray values belonging to one scale together. Thus one scale contains eight orientations. This processing is described as below:

$$GJD_1 = \{u_{(1,1)_{01}},...,u_{(1,1)_{25}},...,u_{(1,8)_{01}},...,u_{(1,8)_{25}}\};$$

$$GJD_2 = \{u_{(2,1)_{01}},...,u_{(2,1)_{25}},...,u_{(2,8)_{01}},...,u_{(2,8)_{25}}\};$$

$$GJD_3 = \{u_{(3,1)_{01}},...,u_{(3,1)_{25}},...,u_{(3,8)_{01}},...,u_{(3,8)_{25}}\}; \quad (7)$$

$$GJD_4 = \{u_{(4,1)_{01}},...,u_{(4,1)_{25}},...,u_{(4,8)_{01}},...,u_{(4,8)_{25}}\};$$

$$GJD_5 = \{u_{(5,1)_{01}},...,u_{(5,1)_{25}},...,u_{(5,8)_{01}},...,u_{(5,8)_{25}}\};$$

where every GJD_i is called one Gabor Jet Descriptor in scale i with 25×8 components, and every $u_{(1,1)_{01}}$ stands for the mean of first block in first scale and first orientation.

To make full use of the discrimination of GJD sufficiently, the dimension reduction should be taken. LDA method is an ideal pattern classification approach. However, to avoid the problem of small sample size problem, the Modified Fisher (MF) criterion function [20] is used as Eq. (8):

$$\hat{J}(\Phi) = \frac{\Phi^{\mathrm{T}} S_B \Phi}{\Phi^{\mathrm{T}} S_{\mathrm{T}} \Phi} \quad (8)$$

$$S_T = S_W + S_B \quad (9)$$

where S_B and S_W are the scatter matrix of between-class and within-class [20]. The parameter Φ is the projective vector, and S_T denotes the total scatter matrix as expressed in Eq. (9)

For every GJD of training thermal face images, we implement MF operation to reduce the dimension. Finally, we get the dimension reduced feature vector $GJDR_{i\ ,\{i=1,...,5\}}^{k}$ as follows:

$$GJDR_1^k = \{f_{11}^k, f_{12}^k,..., f_{1g_1}^k\};$$

$$GJDR_2^k = \{f_{21}^k, f_{22}^k,..., f_{2g_2}^k\};$$

$$GJDR_3^k = \{f_{31}^k, f_{32}^k,..., f_{3g_3}^k\}; \quad (10)$$

$$GJDR_4^k = \{f_{41}^k, f_{42}^k,..., f_{4g_4}^k\};$$

$$GJDR_5^k = \{f_{51}^k, f_{52}^k,..., f_{5g_5}^k\};$$

where f_{ij}^k is the component of every $GJDR_i^k$. Because of the different distribution properties, the dimensions g_i of $GJDR_i^k$ are different after using MF operation. The diagram of the above stages of down sampling is shown in Figure 4.

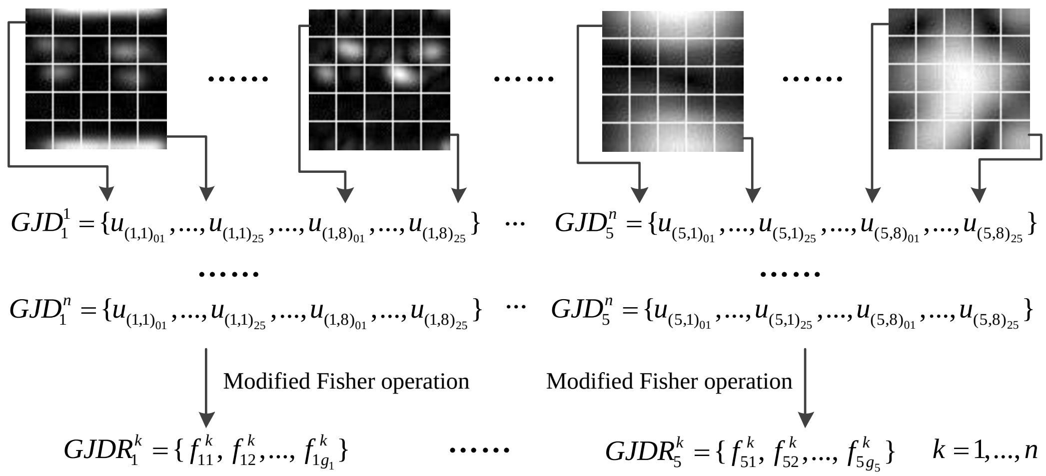

Figure 4. The Diagram of the Two Stages of Down Sampling

The 40 magnitude images are divided into 25 blocks at the same time, and the mean gray value of every block compose the feature component of GJD. After using MF operation on all the training sample's $GJDs$ in 5 scales, the dimension reduced feature vector $GJDRs$ are acquired for matching. This approach will make full use of the superiority of the different scales of Gabor wavelets magnitude representation, and better than that of putting all the five scales' feature into one vector together. It will develop the efficiency of scales of Gabor wavelet representation, and make the dimension reduction vector has much more discrimination.

2.3 Matching based on Borda Count

The Borda Count is a single-winner election method in which voters rank candidates in order of preference. It determines the winner of an election by giving each candidate a certain number of points corresponding to the position in which he or she is ranked by each voter. Once all votes have been counted the candidate with the most points is the winner. BC matching has been used in face recognition [19], and in that literature each GJD is a voter which is considered as an individual classifier. In our proposed approach, after obtaining dimension reduced feature vector $GJDR$, L2 norm shown in Eq. (11) is used to evaluate the distance of the $GJDR_j^i$ and $GJDR_j^k$.

$$D(GJDR_j^i, GJDR_j^k) = \sqrt{\sum_{p=1}^{g_j} (j_{jp}^i - f_{jp}^k)^2},\ i \in \{1,...,n\} \tag{11}$$

where g_j stands for the dimension of the j th scale feature vector, and $GJDR_j^k$ denotes the template of sample k, $GJDR_j^i$ is the feature vector of testing sample i, n is the total samples in testing database.

For the distance result, we give the n testing samples for template $GJDR_j^k$. The smaller the better. Eventually, we acquire the order vector for every template vector as given in Eq. 12:

$$
\begin{aligned}
R_1 &= \{r_1^1, ..., r_1^{n_t}, ..., r_1^{c*n_t}\};\\
R_2 &= \{r_2^1, ..., r_2^{n_t}, ..., r_2^{c*n_t}\};\\
R_3 &= \{r_3^1, ..., r_3^{n_t}, ..., r_3^{c*n_t}\};\\
R_4 &= \{r_4^1, ..., r_4^{n_t}, ..., r_4^{c*n_t}\};\\
R_5 &= \{r_5^1, ..., r_5^{n_t}, ..., r_5^{c*n_t}\};
\end{aligned} \tag{12}
$$

where n_t and c denote the sample number for testing and the class number of database respectively ($n = c * n_t$), and r_i^j denotes the order number of testing sample j. BC matching is carried out as Eq. (13):

$$B_j(x) = \sum_{i=1}^{5} w_i * r_i^j,\ j = 1, ..., c * n_t. \tag{13}$$

where $w_i = 1/5$ is the weight of every scale.

3. Experimental Results and Analysis

In this section, we first introduce the recent thermal face database and then give the comparison with many other existing thermal face recognition methods. Furthermore, the recognition performance based on GMFB method is shown.

3.1. The NVIE Thermal Database

Proposed algorithm for thermal face image is tested in the Natural Visible and Infrared facial Expression (termed NVIE) database which is constructed by The Key Laboratory of Computing and Communication Software of Anhui Province (CCSL). It contains six different expressions of more than 100 subjects, and is recorded simultaneously by a visible and an infrared thermal camera with illumination provided from three different directions. The posed database also includes expression image sequences with and without glasses [26]. We utilize the sub-database including 90 classes, which contains 12 samples with all six expressions, to test the proposed approach and the other existing methods. The experiments of different training and testing numbers are also given.

3.2. Recognition Performance

3.2.1. Comparisons with the Existing Thermal Face Recognition Methods

Initially, we compare the proposed method GMFB with other methods such as PCA, LDA, KPCA, LBP, SIFT, SURF, GJD_LDA, GJD_PCA and GJD_BC. These results are based on 5 training samples and 7 testing samples. In our experiment, the thermal face images are normalized into gray scale and the size of 80 × 80 pixels.

Table 1. The Recognition Performance of Different Approaches

NO.	Method		EER(%)
1	PCA	2004 [10]	14.90
2	LDA	2004 [10]	9.84
3	KPCA	2008 [11]	9.66
4	LBP	2009 [13]	19.22
5	SIFT	2010 [12]	13.75
6	SURF	2012 [5]	33.20
7	GJD_PCA	2002 [18]	12.56
8	GJD_LDA	2002 [18]	6.62
9	GJD_BC	2007 [19]	5.92
10	Proposed_GMFB		4.01

We give the Equal Error Rate (EER) and the Receiver Operator Characteristic (ROC) [1] curve in Table 1 and Figure 5. We can see the proposed algorithm GMFB gets a good recognition result on the NIVE database at EER 4.01%. Due to the histogram of local binary for thermal image, the Local matching-based method LBP doesn't show its excellent performance. The global matching methods SIFT and SURF didn't exhibit very well either. Because only the temperature could be shown in the thermal image, the interest points are not very sufficient. However, dimension reduction based method is useful to find the main direction of the training data. After projecting to another space, it will be easier to distinguish inter-class samples. That's why the performance of LDA and KPCA are a little better. In [5], SURF has better result than that in NVIE thermal database, that's because we use only the face region for SIFT and SURF computation and they are based on the whole face image. Usually, using the whole image for matching in the real application system is not very practical, because of that thermal face image, the temperature is influenced easily in the part of hair, neck and clothes, even changes due to the thick clothes. In what follows, we compare the proposed GJD-based method with other similar methods.

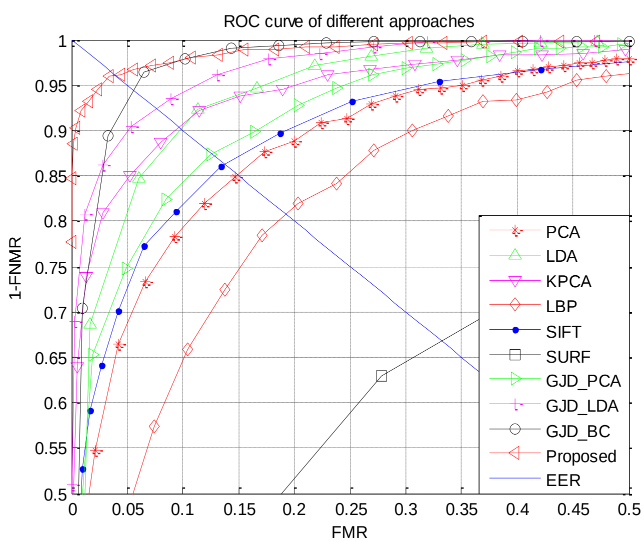

Figure 5. The ROC Curve of Different Thermal Face Recognition Approaches

3.2.2. The Comparison of the GJD-based Methods

GJD_PCA and GJD_LDA mainly focus on dimension reduction. From Table 1 and Figure 5, GJD_LDA shows better performance than GJD_PCA obviously. GJD_BC which takes eight orientations as feature directly and uses BC method for matching gives better result than GJD_LDA and GJD_PCA. Proposed method GMFB shows the best recognition result, which not only uses BC matching method, but also implements MF dimension reduction algorithm for Gabor wavelet representation in every scale.

In order to disclose the relationship between the training number and the recognition performance, classification experiments are performed under a series of different training numbers. The total number of samples for every class is fixed to 12. The p images are randomly selected from each class to construct the training data set, and the remaining images being used as the testing images. To ensure sufficient training, a value of at least 2 is used for p. Table 2 shows the EER of different approaches in different training parameters. We can see that the proposed method outperforms the other methods in terms of recognition accuracy. Also in Table 2, we can notice that the number of training influences the recognition performance largely. The training numbers 4, 5 or 6 are the better choices. When p = 9 or 10, there are only 3 or 2 samples for testing, so it just has much more theoretical value but little practical.

Table 2. Comparison of Different Approaches in Terms of EER (%)

p	GJD_PCA	FJD_LDA	GJD_BC	Proposed
2	15.17	10.06	9.32	12.85
3	14.42	9.17	8.98	5.32
4	13.32	7.99	6.69	4.95
5	12.56	6.62	5.92	4.01
6	12.61	6.92	5.17	3.52
7	12.02	6.01	5.29	3.85
8	11.68	5.58	6.44	4.35
9	12.06	5.68	4.64	4.28
10	11.98	5.04	3.71	4.46

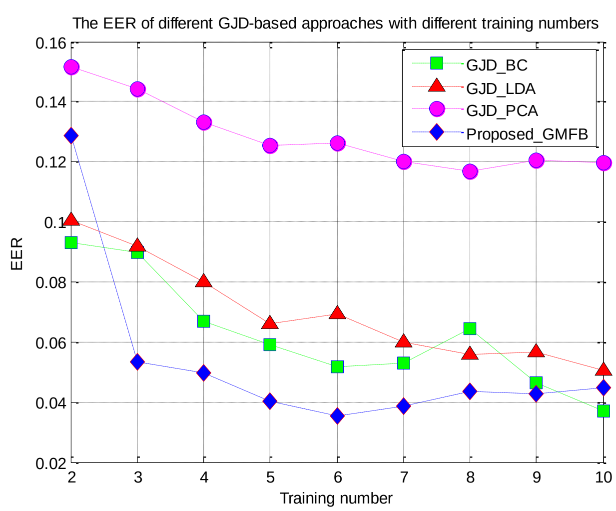

Figure 6. The EER of Different GJD-based Approaches with Different Training Numbers

From Figure 6, we can see that the proposed method GMFB shows the best EER value after training number 3. In the training number 2, it is not efficiency to reduce the dimension under MF operation. The EER of different approaches become worse as the training number increasing and testing number decreasing. But the trends are different. The relative better training number for this NVIE sub-database can be set to 5 or 6.

4. Conclusion

In this paper, we have presented a novel thermal face recognition approach, namely GMFB. The proposed method utilized Gabor Jet Descriptor (GJD) as well as modified Fisher criteria in order to reduce the dimension of every scale. Moreover, Borda count (BC) matching method is used to get a higher matching score. The results based on NVIE thermal face database show that the proposed method outperforms the state-of-the-art methods.

Acknowledgements

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References

[1] 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", Multimed. Tools Appl., **(2012)**, pp. 1-20.
[2] H. Sellahewa and S. Jassim, "Image-Quality-Based Adaptive Face Recognition", IEEE Trans. Instrum. Meas., vol. 59, no. 4, **(2010)**, pp. 805-813.
[3] A. K. Jain, K. Nandakumar and A. Nagar, "Biometric Template Security", Eurasip. J. Adv. Sign. Process., vol. 8, no. 2, **(2008)**, pp. 1-17.
[4] 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.
[5] G. Hermosilla, J. Ruiz-Del-Solar, R. Verschae and M. Correa, "A Comparative Study of Thermal Face Recognition Methods in Unconstrained Environments", Pattern Recognit., vol. 45, no. 7, **(2012)**, pp. 2445-2459.
[6] D. A. Socolinsky and A. Selinger, "Thermal Face Recognition over Time", Proceedings of the 17th International Conference on Pattern Recognition, Cambridge, United kingdom, **(2004)** August 23-26, pp.187-190.
[7] S. G. Kong, J. G. Heo, F. Boughorbel, Y. Zheng, B. R. Abidi, A. M. Y. Koschan and M. A. Abidi, "Adaptive Fusion of Visual and Thermal Ir Images for Illumination-Invariant Face Recognition", J. Comput. Vision, vol. 71, no. 2, **(2007)**, pp. 215-233.
[8] A. K. Jain, B. Klare and U. Park, "Face Recognition: Some Challenges in Forensics", Proceedings of 2011 IEEE International Conference on Automatic Face and Gesture Recognition and Workshops, Santa Barbara, CA, United states, **(2011)** March 21-25, pp. 726-733.
[9] Y. Kim, J. H. Yoo and K. Choi, "A Motion and Similarity-Based Fake Detection Method for Biometric Face Recognition Systems", IEEE Trans. Consum. Electron., vol. 57, no. 2, **(2011)**, pp. 756-762.
[10] D. A. Socolinsky and A. Selinger, "Thermal Face Recognition in an Operational Scenario", Proceedings of 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Washington, DC, United states, **(2004)** June 27-July 2, pp. 1012-1019.
[11] S. Desa and S. Hati, "IR and Visible Face Recognition Using Fusion of Kernel Based Features", Proceedings of the 19th International Conference Pattern Recognition, Tampa, FL, United states, **(2008)** December 8-11, pp. 1-4.
[12] G. Hermosilla, P. Loncomilla and J. Ruiz-Del-Solar, "Thermal Face Recognition Using Local Interest Point Sand Descriptors for HRI Applications", Lect. Notes Comput. Sci., 6556, LNAI, **(2010)**, pp. 25-35.

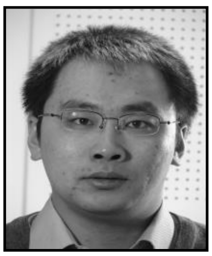
[13] H. Méndez, C. S. Martín, J. Kittler, Y. P. Calana and E. García-Reyes, "Face Recognition With LWIR Imagery Using Local Binary Patterns", Lect. Notes Comput. Sci., 5558, **(2009)**, pp. 327-336.
[14] G. Hermosilla, J. Ruiz-del Solar, R. Verschae and M. Correa, "Face Recognition Using Thermal Infrared Images for Human-Robot Interaction Applications: A Comparative Study", Proceedings of the 6th Latin American Robotics Symposium, Valparaiso, Chile, **(2009)** October 29-30, pp. 1-7.
[15] L. Sirovich and M. Kirby, "Low-Dimensional Procedure for The Characterization of Human Face", J. Opt. Soc. Am. A., vol. 4, no. 3, **(1987)**, pp. 519-524.
[16] M. Lades, J. C. Vorbruggen, J. Buhmann, J. Lange, C. von der Malsburg, R. P. Wurtz and W. Konen, "Distortion Invariant Object Recognition in The Dynamic Link Architecture", IEEE Trans. Comput., vol. 42, no. 1, **(1993)**, pp. 300-311.
[17] L. Wiskott, J. M. Fellous, N. Kruger and C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching", IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, **(1997)**, pp. 775-779.
[18] C. Liu and H. Wechsler, "Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition", IEEE Trans. Image Process., vol. 11, no. 4, **(2002)**, pp. 467-476.
[19] J. Zou, Q. Ji and G. Nagy, "A Comparative Study of Local Matching Approach for Face Recognition", IEEE Trans. Image Process, vol. 16, no. 10, **(2007)**, pp. 2617-2628.
[20] L. F. Chen, H. M. Liao, M. T. Ko, J. C. Lin and G. J. Yu, "A New LDA-Based Face Recognition System Which Can Solve The Small Sample Size Problem", Pattern Recognit., vol. 33, no. 10, **(2000)**, pp. 1713-1726.
[21] Y. Freund and R. E. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and An Application to Boosting", J. Comput. Syst. Sci., vol. 55, no. 1, **(1997)**, pp. 119-139.
[22] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Trans. Syst. Man Cybern., SMC-9, vol. 1, **(1979)**, pp. 62-66.
[23] R. O. Duda and P. E. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures", Commun. ACM, vol. 15, no. 1, **(1972)**, pp. 11-15.
[24] J. G. Heo, S. G. Kong, B. R. Abidi and M. A. Abidi, "Fusion of Visual and Thermal Signatures with Eyeglass Removal for Robust Face Recognition", Proceedings of 2004 International Conference on Computer Vision and Pattern Recognition Workshop, **(2004)** June 27-July 02, pp. 122-127.
[25] J. G. Daugman, "Uncertainty Relation for Resolution in Space, Spatial Frequency, and Orientation Optimized By Two-Dimensional Visual Cortical Filters", J. Optical Soc. Amer., vol. 2, no. 7, **(1985)**, pp. 1160-1169.
[26] 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. Multimedia, vol. 12, no. 7, **(2010)**, pp. 682-691.

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@ict.hit.edu.cn.