Neurocomputing 136 (2014) 262–267

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Letters

Generalized Weber-face for illumination-robust face recognition ☆

Yong Wu [a,b], Yinyan Jiang [a,b], Yicong Zhou [c], Weifeng Li [a,b,*], Zongqing Lu [a,b], Qingmin Liao [a,b]

[a] Department of Electronic Engineering/Graduate School at Shenzhen, Tsinghua University, China
[b] Shenzhen Key Laboratory of Information Science and Technology, Guangdong, China
[c] Department of Computer and Information Science, University of Macau, Macau, China

ARTICLE INFO

Article history:
Received 22 September 2013
Received in revised form
26 November 2013
Accepted 6 January 2014
Communicated by Ran He
Available online 23 January 2014

Keywords:
Face recognition
Illumination insensitive representation
Weber-face
Multi-scale information

ABSTRACT

Robust face recognition under uncontrolled illumination conditions is one of the key challenges for real-time face recognition systems. Weber-face (WF) is an illumination insensitive face representation based on Weber' law. In this letter, we develop a generalized Weber-face (GWF) which extracts the statistics of multi-scale information from face images. By assigning different weights to the inner-ground and outer-ground we further develop a weighted GWF (wGWF) version. Based on our experiments on the extended Yale-B and FERET face database we show that the proposed methods are robust to illumination variations and can obtain promising performance comparable with existing approaches.

1. Introduction

As one of the key biometric technologies, automatic face recognition has a range of applications in the field of information security, smart cards, entertainment, law enforcement and surveillance [1]. Though pleasant results have been achieved during the last decade, there are still many challenges in robust face recognition under uncontrolled conditions such as facial expression, age, and viewpoint. These variations in the illumination conditions are frequent and issues demanded to be solved [2,3].

In recent years, a number of face recognition approaches with illumination invariant have been proposed. They could be devided into four main categories. The first category handles the illumination normalization problem using traditional image processing methods such as Histogram Equalization (HE) [4], Gamma Intensity Correction [5], and Homomorphic filtering approach [6]. The second category attempts to learn a face model of the possible illumination variations from the illumination samples. Batur and Hayes [7] proposed a segmented linear subspace model for illumination robust face recognition. Georghiades et al. [8] made use of Illumination Cone and Zhang and Samaras [9] used the spherical harmonics representation for face recognition under variable lightings. This category requires a lot of training images and is not practical for applications. The third category attempts to find illumination invariant features like transformation domain features [10], local binary pattern (LBP) [11], local ternary Patterns (LTP) [12], etc. The fourth category tries to find illumination invariant representation of the face image. Gradientface (GF) [13], single scale Retinex (SSR) approach [14] and self-quotient image (SQI) [15] are representatives of this category. However, the recognition experiment on a face database with illumination variations shows that none of above is a sufficient illumination-invariant representation [16].

In [17], we proposed a Weber-face (WF) approach, an illumination insensitive representation based on Weber's law. However, WF considers only the center pixel and its eight nearest pixels. To overcome this weakness, this letter introduces a generalized Weber-face (GWF) and a weighted GWF (wGWF) which extend the WF from pixel-level to patch-level and from single-scale to multi-scale. GWF has the following characteristics: firstly, patch-based WF is a generalized version which can extract multi-scale information of face images; secondly, patch-based WF allows for the use of statistics, such as mean, variance and median for improving the noise robustness; thirdly, when the statistics satisfies some condition, patch-based WF can be proved as an illumination insensitive representation. These characteristics of patch-based WF can help to improve illumination-robust face recognition performance.

☆This work was partially supported by the Macau Science and Technology Development Fund under Grant no. 017/2012/A1 and by the Research Committee at University of Macau under Grant nos. SRG007-FST12-ZYC, MYRG113(Y1-L3)-FST12-ZYC and MRG001/ZYC/2013/FST.

* Corresponding author at: Department of Electronic Engineering/Graduate School at Shenzhen, Tsinghua University, China.
E-mail addresses: wuyong11@mails.tsinghua.edu.cn (Y. Wu), jiangyy12@mails.tsinghua.edu.cn (Y. Jiang), yicongzhou@umac.mo (Y. Zhou), Li.Weifeng@sz.tsinghua.edu.cn (W. Li), luzq@sz.tsinghua.edu.cn (Z. Lu), liaoqm@tsinghua.edu.cn (Q. Liao).

0925-2312/$ - see front matter
http://dx.doi.org/10.1016/j.neucom.2014.01.006

2. Weber's law and Weber-face

Weber's law reveals that the ratio of the perceptual increment threshold to the background intensity is a constant and it can be expressed as

$$\frac{\Delta I}{I}=k, \tag{1}$$

where I represents the background intensity, ΔI represents the perceptual increment threshold, and k is the Weber fraction. Weber's law reveals that, when the background intensity is neither strong nor weak, the perceptual increment changes with the background intensity, not in absolute term.

In [17], we proposed an illumination insensitive representation called "Weber-face". WF is defined by

$$\mathrm{WF}(x,y)=\arctan\left(\alpha\sum_{i\in A}\sum_{j\in A}\frac{f(x,y)-f(x-i\Delta x,y-j\Delta y)}{f(x,y)}\right), \tag{2}$$

in which $A=\{-1,0,1\}$, and $f(x,y)$ is the intensity value of the pixel at location (x,y). The arctangent function is a normalization function and the parameter α is a weight coefficient for adjusting the relativity between the intensity difference and current center pixel. WF is justified to be an illumination insensitive representation of the original face image based on Lambertian reflectance model [17], which can be expressed as

$$f(x,y)=r(x,y)i(x,y), \tag{3}$$

where $r(x,y)$ is its reflectance which depends on characteristics of the face surface and $i(x,y)$ denotes its illumination that is generally characterized by slow spatial variations.

3. Proposed methods

3.1. Generalized Weber-face

In fact, we can rewrite the core component of WF as

$$\sum_{i\in A}\sum_{j\in A}\frac{f(x,y)-f(x-i\Delta x,y-j\Delta y)}{f(x,y)}=p\frac{f(x,y)-\mu_{f(x,y)}}{f(x,y)}, \tag{4}$$

in which $p=8$ is the number of neighbor pixels around location (x,y) and $\mu_{f(x,y)}$ is the mean of intensity values of these p neighbor pixels around location (x,y). The ratio $(f(x,y)-\mu_f(x,y))/f(x,y)$ reveals the relative change of Weber's law. However, WF considers only the pixel at the location (x,y) and its eight nearest pixels. Here, we generalize the WF into a patch-based version called the generalized Weber-face (GWF).

We define the inner-ground and the outer-ground within a template as shown in Fig. 1. The GWF is defined by

$$\mathrm{GWF}(x,y)=\arctan\left(\alpha\frac{S(f_I(x,y))-S(f_O(x,y))}{S(f_I(x,y))}\right), \tag{5}$$

where O and I are sets of outer-ground and inner-ground coordinates surrounding coordinate (x,y). $f_O(x,y)$ are the pixel values in outer-ground of coordinate (x,y) and $f_I(x,y)$ are the pixel values in inner-ground of coordinate (x,y). $S(\phi)$ is a statistics of ϕ that satisfies $S(k\phi)=kS(\phi)$ when k is a constant value. Like the Weber-face, the fraction is unbounded, therefore we also adopt an arctangent function to make normalization and α is a parameter for magnifying or shrinking the ratio between the difference of the statistic of the outer-ground and inner-ground pixels and that of the inner-ground pixels.

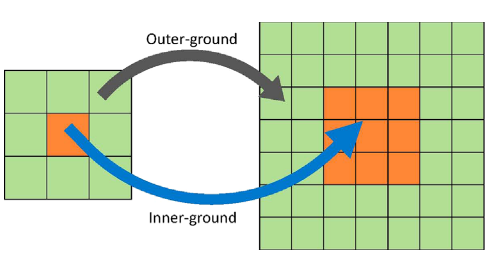

Fig. 1. The relationship between the WF and the GWF, where the size of GWF template is 7×7 and that of inner-ground is 3×3.

Next, we prove that GWF is an illumination insensitive representation of the image f based on the Lambertian reflectance. Similar to Eq. (3), we have

$$f_O(x,y)=r_O(x,y)i_O(x,y), \tag{6}$$

and

$$f_I(x,y)=r_I(x,y)i_I(x,y). \tag{7}$$

in which the illumination component $i(x,y)$ varies slowly in local areas except for the shadow boundaries, i.e.,

$$i_O(x,y)\approx i(x,y),\quad i_I(x,y)\approx i(x,y). \tag{8}$$

By substituting Eqs. (6)–(8) into Eq. (5), we have

$$\begin{aligned}\mathrm{GWF}(x,y)&\\ &=\arctan\left(\alpha\frac{S(r_I(x,y)i_I(x,y))-S(r_O(x,y)i_O(x,y))}{S(r_I(x,y)i_I(x,y))}\right)\\ &\approx\arctan\left(\alpha\frac{S(r_I(x,y)i(x,y))-S(r_O(x,y)i(x,y))}{S(r_I(x,y)i(x,y))}\right).\end{aligned}$$

Due to $S(k\phi)=kS(\phi)$, $GWF(x,y)$ can be represented as

$$\begin{aligned}\mathrm{GWF}(x,y)&\\ &=\arctan\left(\alpha\frac{i(x,y)S(r_I(x,y))-i(x,y)S(r_O(x,y))}{i(x,y)S(r_I(x,y))}\right)\\ &=\arctan\left(\alpha\frac{S(r_I(x,y))-S(r_O(x,y))}{S(r_I(x,y))}\right).\end{aligned}$$

From the above equation, we can observe that $\mathrm{GWF}(x,y)$ is an illumination insensitive representation of the original face image $f(x,y)$ similar to the WF. This is because $\mathrm{GWF}(x,y)$ depends only on the reflectance component r and has nothing to do with the illumination component i.

3.2. Weighted GWF

In Eq. (5), $S(f_I(x,y))$ and $S(f_O(x,y))$ have the same weight α. In fact, we can adopt different weights to offer users the more flexibility in real applications. Therefore we further propose a weighted version of the GWF, named as the weighted GWF (wGWF), i.e.,

$$\mathrm{wGWF}(x,y)=\arctan\left(\frac{\alpha S(f_I(x,y))-\beta S(f_O(x,y))}{S(f_I(x,y))}\right), \tag{9}$$

where a separate weight parameter β is added. Experiments later in this paper will show that the wGWF can obtain better results compared with the WF and GWF.

3.3. Implementation

As mentioned in [17], the Gaussian filter can mitigate the side-effect of shadow boundaries, therefore we implement GWF and wGWF after the Gaussian filter as in [17]. Table 1 summarizes the implementation of the wGWF. In our experiments, the mean is adopted as the statistics.[1] Given the size of template is $M\times M$ and the size of inner-ground is $N\times N$, $S(f'_I(x,y))$ and $S(f'_O(x,y))$ are

[1] It is not limited to the use of the mean as the statistic, and other statistic, such as the median and variance, can also be used.

computed as

$$S(f_I'(x,y)) = \frac{1}{N^2}\sum_{(x,y)\in I} f(x,y), \tag{10}$$

and

$$S(f_O'(x,y)) = \frac{1}{M^2 - N^2}\sum_{(x,y)\in I} f(x,y). \tag{11}$$

It is easy to find Eqs. (10) and (11) revert to the defined in Eq. (2) Weber-face when $M=3$ and $N=1$.

4. Experiments

We carried out our experiments on the extended Yale-B face database and the FERET face database to illustrate the effectiveness of the GWF and wGWF.

The extended Yale face database B is an updated version of the Yale face dataset B. It contains 38 subjects under 9 poses and 64 illumination conditions. In both cases the images are divided into five subsets according to the angle between the light source direction and the central camera axis. The FERET database contains the gallery set Fa (1196 images from 1196 subjects) and four probe sets among which subset Fc (under variations in illumination, 194 images from 194 subjects). In our experiments, all face images from the extended Yale-B database are properly aligned, cropped and resized to 120×120, and the FERET database 128×128. The standard deviation σ of the Gaussian filter in the WF, GWF and wGWF is 1.5 (Fig. 2).

In the experiments, we preprocessed the images with different methods and used LBP operator on the preprocessed images as the feature and took the nearest histogram intersection distance as the classifier rule.

Table 1
Implementation of wGWF.

Input: A face image f
Output: The Weighted GWF (wGWF) of f
1. Smoothen f with a Gaussian filter:
$f' = f * g(x,y,\sigma)$,
where $*$ is a convolution operator and
Gaussian kernel function $g(x,y,\sigma) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$,
2. Process f' with wGWF operator:
(1) Calculate the statistics of inner-ground of f':
$S(f_I'(x,y))$ using Eq. (10).
2) Calculate the statistics of outer-ground of f':
$S(f_O'(x,y))$ using Eq. (11).
(3) Calculate wGWF:
$\text{wGWF}(x,y) = \arctan\left(\frac{\alpha S(f_I'(x,y)) - \beta S(f_O'(x,y))}{S(f_I'(x,y))}\right)$.

Effect of sizes of the inner-ground and the outer-ground. Fig. 3(a) shows the recognition rates of different sizes of inner-ground and outer-ground in the extended Yale-B subset 5 using the method of wGWF. We can find that the recognition rate does not reach the highest when the inner-scale and the outer-scale are both 1, i.e., $M=3$ and $N=1$, which is equivalent to the Weber-face. A slightly larger scale may extract more discriminative information and eliminate more noise, and thus achieve better performance. However, the scale cannot be too large. The illumination component in too large scale would not be approximately equal in Eq. (8) so that it is difficult to guarantee the illumination insensitive representation of the GWF. According to the above results, we obtain a relatively higher recognition rate (95.66% for the subset 5) when the inner-scale is 3 and the outer-scale is 2, i.e., $M=7$ and $N=3$, which are the parameter settings in the following experiments.

Effect of the weights of wGWF. Fig. 3(b) illustrates the recognition rates for various weights in extended Yale-B subset 5 with the wGWF. The recognition rate is affected by the weights α and β. Eq. (9) can be reformulated as

$$\text{wGWF}(x,y) = \arctan\left(\alpha\frac{S(f_I(x,y)) - \frac{\beta}{\alpha}S(f_O(x,y))}{S(f_I(x,y))}\right), \tag{12}$$

According to Eq. (12), α is the parameter to adjust the normalization with the arctan function as mentioned in [17]. The ratio β/α is for adjusting the statistic between the outer-ground and the inner-ground because of the various number of pixels in the outer-ground and the inner-ground. Better results are generally obtained when the ratio β/α is slightly more than 1.

Effect of the standard deviation σ in the Gaussian filter. The standard deviation σ can be viewed as a measure of the Gaussian filter. The Gaussian filter is adopted in front of the GWF method with the purpose of noise removal. Therefore, the standard deviation σ depends mainly on the noise in the face image. From the point of the view of frequency domain, the Gaussian filter removes the noise in high frequency and the GWF method decreases the influence of different illumination components in low frequency. The standard deviation σ in the Gaussian filter decides the bandwidth. Like Laplacian of the Gaussian filter, larger σ will help to eliminate the noise in high frequency. However, σ should not be too large in case too much high-frequency face information is weakened at the same time. Experimental results demonstrate that setting $\sigma = 1.5$ can achieve higher recognition rate.

Fig. 4 shows the faces for different images of the same person using different methods, where the first column "ORI" shows the original images without any preprocessing under different illumination conditions. Column "HE" shows the results of Histogram Equalization (HE) [4]. Column "LoG" shows the results of the Laplacian of Gaussian where the standard deviation σ is 1.5. Column "PP" represents the preprocessing results of a state-of-the-art method [18]. Column "WF" shows the results of the Weber-

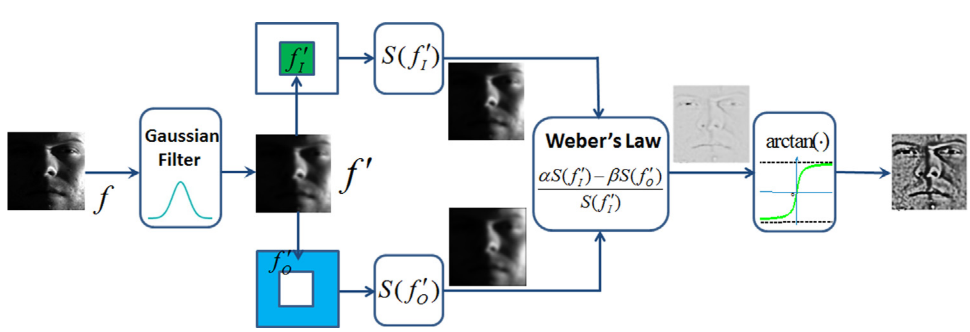

Fig. 2. Illustration of the computation of wGWF, while taking the mean as the statistic.

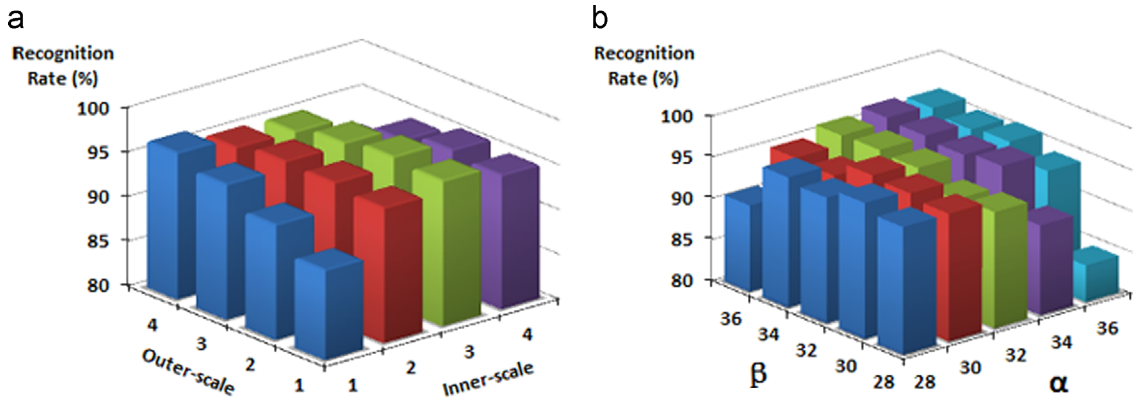

Fig. 3. Breakdown of recognition rates on the Subset 5 in the Extended Yale-B for the various scales and weights using the wGWF. (a) The various scales where inner-scale$=N$ and outer-scale$=(M-N)/2$; (b) the various weights when $M=7$ and $N=3$.

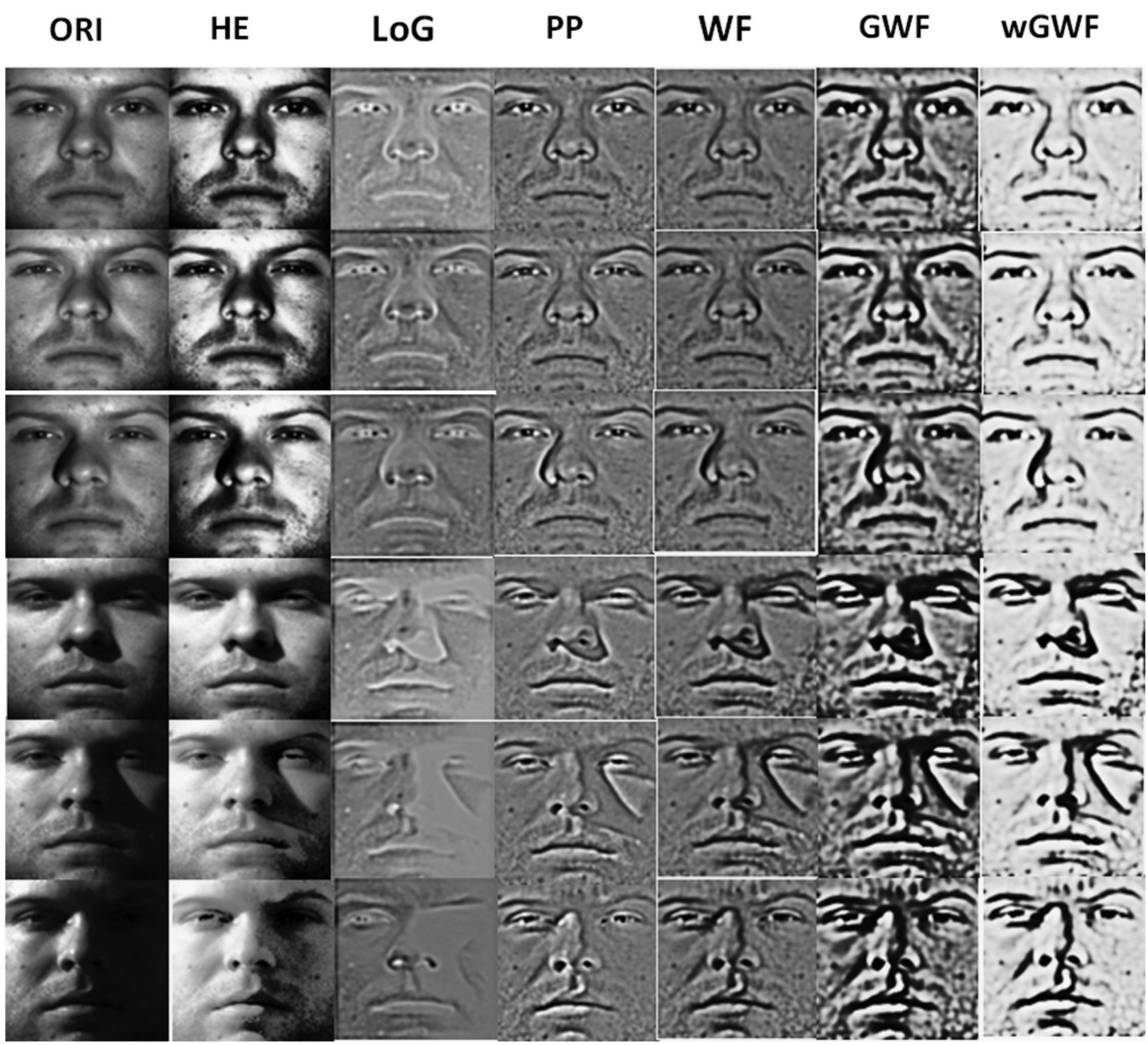

Fig. 4. The faces for different images of the same person processed by different methods.

face [17]. Column "GWF" and "wGWF" are the results of our proposed generalized Weber-face and weighted GWF respectively. We adjusted the parameters of each method carefully according to the original paper, where $\alpha=4$ in the Weber-face and $\alpha=16$ in the GWF ensure the equivalence between the Weber-face and the GWF when $M=3$ and $N=1$. We can find that the results of the

Table 2
Recognition rates (%) on extended yale face database B.

Method	S1	S2	S3	S4	S5	Average
ORI	100	100	96.92	61.03	34.87	78.56
HE	100	100	96.92	60.46	36.97	78.87
LoG	100	100	100	96.57	85.15	96.34
PP	100	100	99.56	94.30	79.13	94.60
WF	100	100	99.78	96.39	90.06	97.25
GWF	**100**	**100**	**99.78**	**97.15**	**92.86**	**97.96**
wGWF	**100**	**100**	**100**	**97.53**	**95.66**	**98.64**

Table 3
Recognition rates (%) on FERET-Fc database.

Method	ORI	HE	LoG	PP	WF	GWF	wGWF
Fc	80.93	77.32	98.45	98.45	98.45	**98.97**	**99.48**

GWF and wGWF methods are insensitive to illumination variation, compared with the method “HE” and “LoG”. The images processed by the GWF have better contrast between significant parts of the face features and the rest with less discriminative information. Moreover, wGWF eliminates most of the undiscriminating parts when selecting the appropriate weights.

Table 2 shows the recognition rates in the extended Yale-B database using different methods. The wGWF performs better than GWF, and achieves 20.08%, 19.77%, 2.3%, 4.04%, and 1.39% higher average recognition rate than the average rates of the first five methods. Both the GWF and wGWF have better performance than other methods in each subset. Table 3 shows the recognition rates on the FERET-Fc database. Both the GWF and wGWF achieve excellent recognition performance.

5. Conclusion

The proposed GWF and wGWF are generalized multi-scale versions of the Weber-face. They have been proved to be illumination insensitive representations under the Lambertian reflectance model similar to Weber-face. They can extract multi-scale information and obtain more discriminative information with larger contrast between significant parts of face feature and the undiscriminating parts. Experimental results on extended Yale-B and FERET database have demonstrated that our proposed GWF and wGWF show better performance than several other approaches. This provides new insights into the role of robust preprocessing method under uncontrolled illumination conditions for face recognition.

References

[1] W. Zhao, R. Chellappa, P.J. Phillips, A. Rosenfeld, Face recognition: a literature survey, ACM Comput. Surv. (CSUR) 35 (2003) 399–458.

[2] Y. Adini, Y. Moses, S. Ullman, Face recognition: the problem of compensating for changes in illumination direction, IEEE Trans. Pattern Anal. Mach. Intell. 19 (1997) 721–732.

[3] W. Zou, P. Yuen, R. Chellappa, Low-Resolution Face Tracker Robust to Illumination Variations, IEEE Trans. Image Process 22 (2013) 1726–1739.

[4] S.M. Pizer, E.P. Amburn, J.D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. ter Haar Romeny, J.B. Zimmerman, K. Zuiderveld, Adaptive histogram equalization and its variations, Comput. Vision Graph. Image Process. 39 (1987) 355–368.

[5] S. Shan, W. Gao, B. Cao, D. Zhao, Illumination normalization for robust face recognition against varying lighting conditions, in: AMFG 2003, IEEE, 2003, pp. 157–164.

[6] R.C. Gonzales, R.E. Woods, Digital Image Processing, 2nd ed., Prentice-Hall, Upper Saddle River, NJ, 2002.

[7] A.U. Batur, M. Hayes, Linear subspaces for illumination robust face recognition, in: CVPR 2001, vol. 2, IEEE, 2001, pp. II-296.

[8] A.S. Georghiades, P.N. Belhumeur, D.J. Kriegman, From few to many: illumination cone models for face recognition under variable lighting and pose, IEEE Trans. Pattern Anal. Mach. Intell. 23 (2001) 643–660.

[9] L. Zhang, D. Samaras, Face recognition from a single training image under arbitrary unknown lighting using spherical harmonics, IEEE Trans. Pattern Anal. Mach. Intell. 28 (2006) 351–363.

[10] C. Xie, M. Savvides, B.V. Kumar, Quaternion correlation filters for face recognition in wavelet domain, in: ICASSP 2005, 2005.

[11] G. Heusch, Y. Rodriguez, S. Marcel, Local binary patterns as an image preprocessing for face authentication, in: FGR 2006, IEEE, 2006, p. 6.

[12] X. Tan, B. Triggs, Enhanced local texture feature sets for face recognition under difficult lighting conditions, IEEE Trans. Image Process. 19 (2010) 1635–1650.

[13] T. Zhang, Y.Y. Tang, B. Fang, Z. Shang, X. Liu, Face recognition under varying illumination using gradientfaces, IEEE Trans. Image Process. 18 (2009) 2599–2606.

[14] D.J. Jobson, Z.-u. Rahman, G.A. Woodell, Properties and performance of a center/surround retinex, IEEE Trans. Image Process. 6 (1997) 451–462.

[15] H. Wang, S.Z. Li, Y. Wang, J. Zhang, Self quotient image for face recognition, in: ICIP'04, vol. 2, IEEE, 2004, pp. 1397–1400.

[16] X. Zou, J. Kittler, K. Messer, Illumination invariant face recognition: a survey, in: BTAS 2007, IEEE, 2007, pp. 1–8.

[17] B. Wang, W. Li, W. Yang, Q. Liao, Illumination normalization based on weber's law with application to face recognition, IEEE Signal Process. Lett. 18 (2011) 462–465.

[18] X. Tan, B. Triggs, Enhanced Local Texture Feature Sets for Face Recognition under Difficult Lighting Conditions, IEEE Transactions on Image Processing 19 (6) (2010) 1635–1650.

Yong Wu received the B.E. degree from Department of Electronics and Information Engineering, Tsinghua University, Beijing, China, in 2011. He is currently working towards the Master degree in electronics engineering at Tsinghua University, Beijing, China. His research interests include applications of image processing and pattern recognition in biometrics.

Yinyan Jiang received the B.E. degree in Electronic Engineering from Tsinghua University, Beijing, China, in 2012. She is currently a master student working on face recognition in Tsinghua University. Her research interests include image processing and pattern recognition in biometrics and super-resolution.

Yicong Zhou received his B.S. degree from Hunan University, Changsha, China, and his M.S. and Ph.D. degrees from Tufts University, Massachusetts, USA, all degrees in electrical engineering. He is currently an Assistant Professor in the Department of Computer and Information Science at University of Macau, Macau, China. His research interests focus on multimedia security, image/signal processing, pattern recognition and medical imaging. Dr. Zhou is a member of the IEEE and SPIE (International Society for Photo-Optical Instrumentations Engineers).

Weifeng Li received the M.E. and Ph.D. degrees in Information Electronics at Nagoya University, Japan, in 2003 and 2006, respectively. He joined the Idiap Research Institute, Switzerland, in 2006, and in 2008 he moved to Swiss Federal Institute of Technology, Lausanne (EPFL), Switzerland, as a research scientist. Since 2010 he has been an associate professor in the Department of Electronic Engineering/Graduate School at Shenzhen, Tsinghua University, China. His research interests lie in the areas of audio and visual signal processing, Biometrics, Human-Computer Interactions (HCI), and machine learning techniques. He is a member of the IEEE and IEICE.

Lu Zongqing received the Ph.D. degree in signal processing from XiDian University Xi'an China in 2007. From 2007 to 2010, he was a postdoctoral fellow at Tsinghua University. Now he is an assistant professor in the Electronic engineering Department of Tsinghua University. His research interests include Image processing, Machine learning.

Qingmin Liao received the B.S. degree in radio technology from the University of Electronic Science and Technology of China, Chengdu, China, in 1984, and the M.S. and Ph.D. degrees in signal processing and telecommunications from the University of Rennes 1, Rennes, France, in 1990 and 1994, respectively.

Since 1995, he has been joining with Tsinghua University, Beijing, China. In 2002, he became Professor in the Department of Electronic Engineering of Tsinghua University. Since 2010, he has been the director of the Division of Information Science and Technology in the Graduate School at Shenzhen, Tsinghua University. He is also affiliated with the Shenzhen Key Laboratory of Information Science and Technology (Director), China. Over the last 30 years, he has published over 100 peer-reviewed journal and conference papers. His research interests include image/video processing, transmission and analysis; biometrics; and their applications to teledetection, medicine, industry, and sports.