https://doi.org/10.2352/ISSN.2470-1173.2018.2.VIPC-252

Efficient Preprocessing and Feature Extraction for Robust Face Recognition

Huda M.S.Algharib; O. Serdar Gedik; Ankara Yildirim Beyazit University; Turkey, Ankara

Abstract

Face recognition in real world environments is mainly affected by critical factors such as illumination variation, occlusion and small sample size. This paper proposes a robust preprocessing chain and robust feature extraction in order to handle these issues simultaneously. The proposed preprocessing chain exploits Difference of Gaussian (DoG) filtering as a bandpass filter to reduce the effects of aliasing, noise and shadows, and then exploits the gradient domain as an illumination insensitive measure. On the other hand, Linear Discriminant Analysis (LDA) is one of the most successful facial feature extraction techniques, but the recognition performance of LDA is dramatically decreased by the presence of occlusion and small sample size (SSS) problem. Therefore, it is necessary to develop a robust LDA algorithm in order to handle these cases. At this point, we propose to combine Robust Sparse Principal Component Analysis (RSPCA) and LDA (RSPCA+LDA). The RSPCA is performed first in order to reduce the dimension and to deal with outliers typically affecting sample images due to pixels that are corrupted by noise or occlusion. Then, LDA in low-dimensional subspaces can operate more effectively. Experimental results on three standard databases, namely, Extended Yale-B, AR and JAFFE confirm the effectiveness of the proposed method and the results are superior to well-known methods in the literature.

Introduction

Face recognition (FR) in complex environmental conditions such as severe illumination variations and occlusions suffers from increase in the intra-class variations that significantly decrease the recognition performance. In case of illumination variation, many facial images belong to the same person appear significantly different; and hence complicate the recognition process [1]. On the other hand, occlusion (caused by sunglasses, scarves, etc.) destroys the key facial landmarks, increases even the distance between two sample images of the same person in the feature space and therefore the task of recognizing faces becomes more and more difficult, as in the case of illumination variation. [2].

Over the past years, Several studies have been conducted in order to deal with each of these factors. Illumination preprocessing [3], illumination insensitive representation [4] 3D face modelling [5] are differentiated methods proposed for illumination related problems. The illumination normalization approaches attempt to make the facial images appear stable under various lighting conditions by normalizing the variation in illumination, whereas the illumination invariant representation methods attempt to extract illumination invariant features or illumination insensitive measure. The 3D face modelling aims to build a generative model that may be exploited to estimate facial images with fixed poses but under different lighting conditions.

On the other hand, in literature there are three classes of approaches proposed to deal with the facial occlusion problem. Modelling-based approaches [6] handle the occlusions in face recognition as a modelling problem. An occluded test image is modeled via linear combination of the training images from all classes, and then the test image is assigned to the class with the minimal modelling error. However, these approaches usually require too many training samples per individual to represent a test image, which are not suitable for real world applications. In the second class of local matching based approaches [8], face images are partitioned into small regions so that the occluded and unoccluded regions of the face can be analyzed separately. The third category of approaches aim to extract features robust to occlusion from face images. In [9], principal component analysis of image gradient orientations (IGO-PCA) has been proposed. The method shows that subspace learning from image gradient orientations rather than subspace learning from pixel intensities is insensitive to outliers such as occlusions.

Illumination variation and occlusion usually coexist in real-world environments. However, most of the researches in the face recognition field are focused on handling these issues independently, with less work focusing on proposing simultaneous solutions. Methods that are robust to one kind of challenge may be ineffective to the other, and therefore, addressing multiple issues together is a big challenge in real-world face recognition.

In this paper, we propose a computationally simple and efficient two step preprocessing approach to handle illumination variation. In the first step of this preprocessing, DoG filtering is exploited as a bandpass filter to suppress the highest and lowest spatial frequencies that mainly stem from noise and lighting variations respectively. In the second step, illumination insensitive measures from gradient domain are extracted using Gradientfaces [10]. The gradient domain has more discriminating power than the pixel domain, due to the fact that it employs derivative and in fact relationships between neighboring pixels. To extract features needed for recognition, we propose to combine RSPCA [11] with LDA [12]. In RSPCA, The L1-norm variance of the input data is maximized, which is intrinsically less sensitive to noise and outliers. For class separation, LDA finds the directions that form the axes that maximize the separation between multiple classes. LDA will not suffer from SSS problem since the dimension reduction is done by RSPCA.

The rest of this paper is organized as follows: Section 2 describes the two-step preprocessing chain. Section 3 explains robust feature extraction based on RSPCA and LDA. To evaluate the effectiveness of the proposed system, large-scale experiments are conducted and the results are shown in Section 4. Finally, Section 5 presents the concluding part of the paper.

The Preprocessing Chain

This section describes a computationally simple and effective preprocessing algorithm that eliminates major effects of illumination variation and noise while remaining the important details of visual appearance that are necessary for recognition.

Difference of Gaussian (DoG) Filtering

In face recognition, DoG is a convenient way to separate the shading induced by face structure that usually contains useful information for face recognition from the effects caused by illumination gradients [26]. In addition, it reduces the effects of aliasing and noise by suppressing highest spatial frequencies [26]. The DoG filter on image I is defined as:

$$I'(x,y) = I * \frac{1}{2\pi\sigma_1^2} e^{-\frac{x^2+y^2}{2\sigma_1^2}} - I * \frac{1}{2\pi\sigma_2^2} e^{-\frac{x^2+y^2}{2\sigma_2^2}} \quad (2.1)$$

Where the value of σ_1 and σ_2 are standard deviation values to be determined depending on the amount of noise and lighting variations in the given dataset. * represents convolution operation.

Gradientfaces

Gradientfaces [10] is an illumination insensitive measure derived from the image gradient domain. The main interesting advantage of gradient domain is that it takes into account the relationships between adjacent pixel points, unlike the pixel domain that ignore such relations. Therefore, it is able to discover the key facial features or the underlying structure of the face image which play important role in recognition. The main equation of this method can be expressed as following [10]:

$$G = \arctan\left(\frac{I_{y-\text{gradient}}}{I_{x-\text{gradient}}}\right), G \in [-\pi, \pi] \quad (2.2)$$

Where $I_{x-\text{gradient}}$ and $I_{y-\text{gradient}}$ are the gradient of image I in x and y directions, respectively.

Figure 1. shows the effectiveness of DoG with Gradientfaces based preprocessing for handling illumination problem in face recognition, since it is robust to lighting variation and noise.

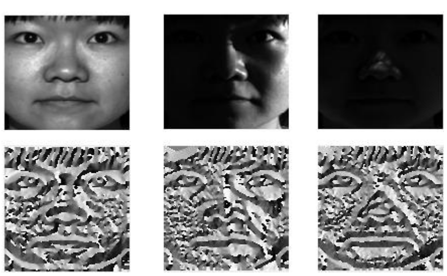


Figure 1: Sample images from the E-YaleB face database, original images (upper row), processed images(lower row).

Feature Extraction

The proposed algorithm utilizes two feature extraction methods, namely RSPCA and LDA, in order to handle occlusion and SSS simultaneously and effectively. The traditional sparse PCA methods suffer from a common drawback - all are based on the classical approach to PCA which mainly aims to maximize the L2-norm variance of the input data, thus, they suffer from the fact that the nature of L2-norm is sensitive to outliers and noises [13]. The presence of outliers and noises in the data increases the variance in an uninformative direction and may consider as a PC direction. To avoid this problem, robust sparse PCA algorithm was proposed in [11] maximizing the L1-norm variance of the input data instead of maximizing the L2-norm variance.

The second technique employed for feature extraction is LDA [12]. LDA has been applied to many applications of pattern recognition and has become one of the most successful techniques. However, this technique suffers from SSS problem when applied to high-dimensional Input data as in face recognition. This is due to the singularity of within-class scatter matrix. Thus, LDA in low-dimensional subspaces such as RSPCA may be more effective, especially in case of the presence of occlusion. The main aim of LDA is the separation of multiple classes of the data once projected upon.

Robust Sparse PCA (RSPCA)

RSPCA aims to gain the maximal L1-norm variance of the data, which is intrinsically less sensitive to noise and outliers [11]. This goal can be achieved by solving the following optimization problem:

$$W^* = \arg_W \max \left\| W^T X \right\|_1, \text{ subject to } W^T W = I_m, \ \|W\|_1 < t, \quad (3.1)$$

Where $X = [x_1, x_2, ..., x_n] \in R^{dxn}$ the input data matrix with *d*-dimensional and *n* samples. Without loss of generality, $\{X_i\}_{i=1}^n$ is assumed to have zero mean. $W = [w_1, w_2, ..., w_m] \in R^{dxm}$ is the projection matrix, where each column w_k of W corresponds to the *k-th* PC of the original data, I_m is the *m*x*m* identity matrix, and $\| \|_1$ denotes the L1-norm of a matrix or a vector.

However, the problem (3.1) needs to simplified because the optimal *i-th* PC w_i varies with different preset number *m* of PCs. In addition, finding a global solution of this problem for $m > 1$ is very difficult. Therefore, the authors of [11] suggest to simplify the problem (3.1) into a series of $m=1$ problems using a greedy search algorithm. That means, (3.1) becomes the following optimization problem:

$$w^* = \arg_W \max \left\| X^T w \right\|_1, \text{ subject to } w^T w = 1, \ \|w\|_1 < t, \quad (3.2)$$

The equation (3.2) for $m>1$ sparse PCs using greedy algorithm can be denoted as $W_{rspca} = \{w_i\}_{i=1}^m$. The feature matrix for training images X can be obtained by :

$$A = W_{rspca}^T X \quad (3.3)$$

Similarly, we can also obtain a feature matrix for the testing images Y by :

$$T = W_{rspca}^{T} Y \qquad (3.4)$$

Figure 2 shows the ability of the RSPCA to reconstruct the occluded face image in gradient domain, where clean images (i.e. without occlusion) from subset 1 of Extended Yale-B dataset are used for training. Images with synthetic occlusion from Subset 3 were used for testing. As can be seen, RSPCA-based reconstruction, it effectively reconstructs the Gradientfaces even in occluded areas.

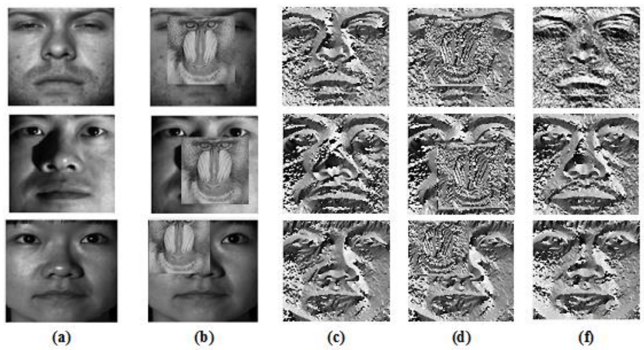


Figure 2: (a) The original face images, (b) the corresponding images with occlusion, (c)-(d) the corresponding images after preprocessing of (a)-(b), and (f) Reconstruction of (d) by RSPCA method with 20 corresponding projection PCs, respectively.

Linear Discriminant Analysis (LDA)

LDA [12] searches for a set of vectors in the underlying space that enables best discrimination among classes. In other words, In other words, LDA defines two measures in order to separate multiple classes well: 1) Within-class scatter matrix, as given by:

$$S_W = \sum_{j=1}^{c} \sum_{i=1}^{N_j} \left(a_i^j - \mu_j\right)\left(a_i^j - \mu_j\right)^T \qquad (3.5)$$

Where a_i^j is the *i-th* sample of class j in the RSPCA training feature matrix A, μ_j is the mean of class j, c is the number of classes, and N_j the number of sample images in class j; and 2) Between-class scatter matrix given by:

$$S_b = \sum_{j=1}^{c} \left(\mu_j - \mu\right)\left(\mu_j - \mu\right)^T \qquad (3.6)$$

Where μ represents the mean of all classes. The goal is to maximize the between-class measure while minimizing the within-class measure. One way to do this is to maximize the ratio:

$$W_{lda} = arg \max_W \left| \frac{W_{lda}^T S_b W_{lda}}{W_{lda}^T S_w W_{lda}} \right| \qquad (3.7)$$

Finally, we project the RSPCA training feature vectors as follow:

$$U = W_{lda}^{T} A \qquad (3.8)$$

Similarly, we project the RSPCA testing feature vectors as follow:

$$V = W_{lda}^{T} T \qquad (3.9)$$

In order to calculate the similarity between two vectors u and v, we have used the Cosine distance denoted by:

$$D_{\cos}(u, v) = \frac{u^T v}{\|u\| \, \|v\|} \qquad (3.10)$$

An overview of the proposed system is depicted in Figure 3.

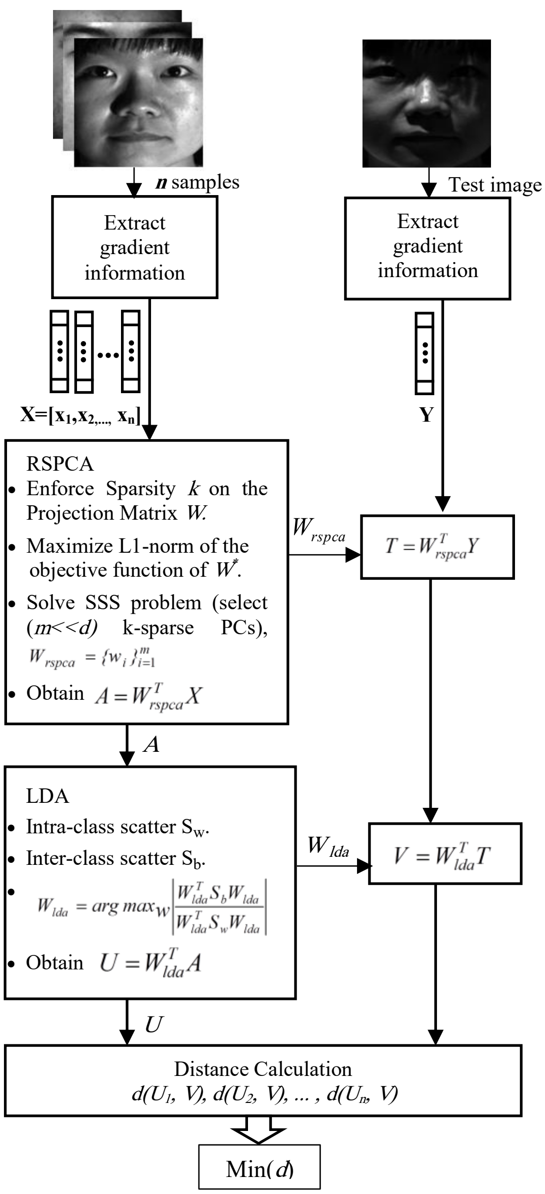


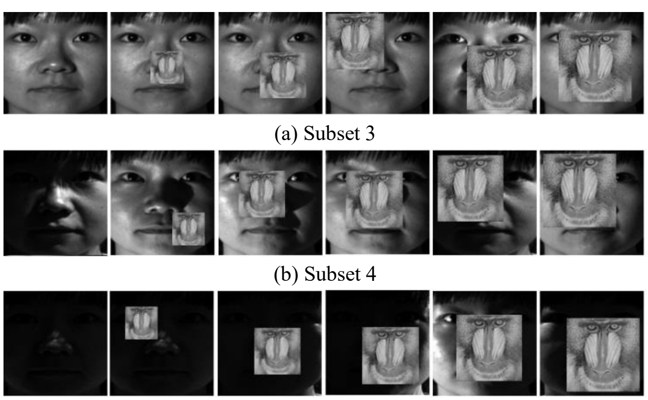
Figure 3: Overview of the system.

Experimental Results

In order to evaluate the performance of the proposed method, many experiments were conducted on three standard face databases, namely Extended Yale-B [15], AR [7] and JAFFE [27]. The Extended Yale-B face database is one of the most challenging databases that exhibits extreme variation in illumination. It consists of still images, in fixed frontal pose, for 38 persons, each having 64 images captured under various illumination conditions. However, this database provides only extreme illumination conditions and assume that there are no occlusion, facial expression, pose and age variations. The AR Face Database [7] contains 70 male and 56 female subjects photographed in two separate sessions held on different days. Each session produced 13 images of each subject, these images were captured under different illuminations, facial expressions and real occlusions. On the other hand, the AR database does not consider important challenges such as pose variations and age variations. The JAFFE database contains 213 images of different facial expressions only (1 neutral+ 6 basic facial expressions) for 10 females, each having 2 to 4 images for each expression.

Experiment 1: Face recognition under varying illumination and random occlusion

In this experiment, we have tested the robustness of the proposed method on Extended Yale-B database with random block occlusion. We use images without occlusion from Subset 1 and 2 (717 images) for training. Images with synthetic occlusions from Subset 3, Subset 4 and Subset 5 are used for testing. Each testing sample will be inserted an unrelated image as block occlusion, and the blocking ratio changes between 10%-50% as illustrated in Figure3.



(a) Subset 3

(b) Subset 4

(c) Subset 5

Figure 3: Sample images from the Extended Yale B database with randomly located occlusions: a) Subset 3, b) Subset 4. c) Subset 5.

In Table 1, we compare our proposed techniques with other existing methods that claim to handle the occlusion problem. As shown in the table, we can see that when the block occlusion ratio is low, all methods can achieve good recognition accuracy. However, when the block occlusion ratio increases, the accuracy of the proposed method still has significant results.

Table 1. Recognition Rates (%) on the Subset 3 of the Extended Yale B Database.

Occlusion ratio	0%	10%	20%	30%	40%	50%
SRC [6]	**100**	**100**	99.8	98.5	90.3	65.3
CRC-RLS [17]	**100**	99.8	93.6	82.6	70.0	52.3
GSRC [18]	**100**	**100**	**100**	99.8	96.5	87.4
RSC [19]	**100**	**100**	**100**	99.8	96.9	83.9
SSR-P[20]	**100**	**100**	**100**	**100**	97.8	85.4
MLERPM [25]	**100**	**100**	**100**	98.3	80.2	30.2
Proposed	**100**	**100**	99.8	99.3	**98**	**97.1**

We have extended our tests to include more challenging subsets: Subset 4 and Subset 5. The recognition results are shown in Table 2 and Table 3, respectively. As can be seen, the proposed method achieves excellent recognition rates on all levels of occlusion and outperforms all the other methods.

Table 2. Recognition Rates (%) on The Subset 4 of The Extended Yale B Database.

Occlusion ratio	0%	10%	20%	30%	40%	50%
SRC[6]	86.3	78.5	70.0	53.2	36.7	28.1
GSRC [18]	95.3	88.8	84.2	76.4	66.5	54.7
SSR-P[20]	97.2	93.4	84.8	68.4	53.4	39.9
SSR-W[20]	99.6	99.8	99.4	99.4	**99.6**	98.1
Proposed	**100**	**100**	**100**	**99.8**	99.2	**99.2**

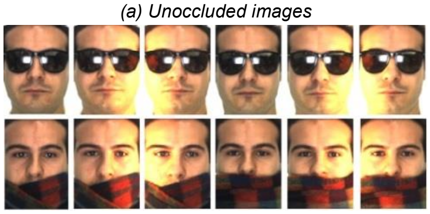
Table 3. Recognition Rates (%) on the Subset 5 of The Extended Yale B Database.

Occlusion ratio	0%	10%	20%	30%	40%	50%
SRC[6]	37.5	26.9	14.3	9.0	7.9	7.3
GSRC [18]	44.2	31.7	32.0	23.8	21.5	17.5
SSR-P[20]	42.6	31.6	23.4	15.3	11.5	10.9
SSR-W[20]	98.3	98.0	97.3	95.8	**95.4**	88.6
Proposed	**99.7**	**99.3**	**98.3**	**97.8**	95.1	**90.8**

Experiment 2: Face recognition with facial disguises and non-uniform illuminations

We also test the proposed method on the AR database [7] where the images include real occlusion with non-uniform illumination changes. In our experiments, we selected the first 50 male subjects and first 50 female subjects, as was done in several papers (e.g., [25]), for a total of 100 classes. For each class, 14 unoccluded face images were used as training, whereas 6 images with sunglasses and 6 images with scarves were chosen for testing (Figure 4). The images are resized to 80×60 pixels and converted to grayscale. Table 4 records the recognition accuracy on the AR dataset.

(a) Unoccluded images



(b) Images occluded by sunglasses and scarves

Figure 4: Cropped images from the AR database used in the experiments.

Table 4. Recognition rates (%) on the AR database

Method	Sunglass	Scarf	Sunglass + Scarf
SRC [6]	87.0	59.5	73.3
CRC [17]	68.5	90.5	79.5
NNCW [22]	88.4	62.2	75.3
RoBM [23]	84.5	80.7	82.6
L1-Lstruct [24]	92.5	69.0	80.8
MLERPM [25]	**98.0**	**97.0**	**97.5**
Proposed	96.5	92.5	94.5

In table 4, DoG +Gradienface with RSPCA+LDA achieves excellent recognition rates compared with many state-of-the art methods. Although the MLERPM achieves the highest recognition rate in this experiment, the performance of this method decreases severely when most part of face area is occluded (i.e. occlusion percent is more than 40%) as shown in Table 1, whereas our method still achieves significant results on all levels of occlusion.

Experiment 3: Face recognition with occlusions in the training and testing sets

Most of the current approaches suppose that occlusions only occur in the testing images and the training images are unoccluded as in our previous experiments. In practical scenarios, the facial occlusion is unpredictable and may occur in both training and testing images. Therefore, this section considers the case that occlusions are present in both the training and testing sets, which makes the recognition process more challenge. We conducted two experiments. In the first one (experiment A), two images with scarves where selected to form the training set and two images with sunglasses images as the testing set (Figure 5). In the second one (experiment B), We conducted vice versa (i.e. two images with sunglasses as training and two images with scarves as testing).

(a) (b)

Figure 5: Sample of occluded images from the AR database used in the experiments A and B.

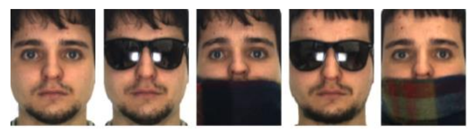
The results are shown in Table. 4.12. Our method outperforms the others by about (6-15)% on average.

Table 5. Recognition rates (%) on the AR database in case of occlusions exist in both training and testing images

Method	Experiment A	Experiment B	AVG
HMM [28]	5.5	6	5.6
PCA+SVM [29]	15	13	14
SRC [6]	17	10	13.5
Proposed	19.5	21	20.3

Experiment 4: Face recognition with small sample size (SSS)

In this section, we have tested the performance of our methods with only 1 training image per person. In the experiment, a subset of 100 persons (50 male and 50 female) from AR face database was chosen. The face images with the most neutral light from the first session (see Figure 6 (a)) were used as training images. The face images with sunglasses and scarf from the first and the second sessions (see Figure 6 (b-e)) were used as testing set.



a b c d e

Figure 6: Images of one person in the AR database. (a) is the face image with the most neutral light from the first session; (b-e) are the face images with sunglasses and scarf from the first and the second sessions.

The results in Table 6, showing that the proposed method is very competitive with well-known benchmark methods in terms of accuracy.

Table 6. Recognition rates (%) on the AR database (sunglasses and scarf occluded faces)

Methods	Session-1		Session-2		AVG
	sunglasses	scarf	sunglasses	scarf	
SRC-block [6]	86.0	87.0	49.0	**70.0**	73.0
SOM [21]	**97.0**	**95.0**	60.0	52.0	76.0
LocPb [14]	80.0	82.0	54.0	48.0	66.0
AWPPZMA [16]	70.0	72.0	58.0	60.0	65
Proposed	89.0	86.0	**67.0**	65.0	**76.8**

Experiment 5: RSPCA+LDA compared with different subspace LDA Methods

The subspace LDA methods are the most successful approaches to avoid SSS problem, where the dimensionality is reduced first and then LDA is applied in low-dimensional subspace. In this experiment, we compare LDA in RSPCA subspace with the most common subspace LDA methods in terms of their recognition rate. The results on a face database that includes facial expressions (i.e. JAFFE database) show that the proposed method can also be applied to recognize face images with facial expression although it was mainly designed to handle illumination variation and occlusion. Only one image with neutral facial expression per person was selected for training, and 6 basic facial expressions (happy, angry, sad, fearful, surprise and disgust) per person was selected for testing as shown in Figure 7.

Figure 7: Sample images from the JAFFE database

The results for experiment 5 are shown in table 7.

Table 7. Recognition rates (%) on the JAFFE database

Subspace LDA methods	Recognition rates (%)
Fisherface [12]	N/A
Complete PCA plus LDA [30]	82.1
IDAface [31]	82.1
BDPCA plus LDA [32]	78.6
RSPCA+LDA (Proposed)	86.7

Conclusion

In this paper, we propose a simple and robust FR scheme by combining robust preprocessing chain with robust feature extraction to handle illumination variation and occlusions at the same time. The preprocessing chain effectively eliminates undesired illumination effects and makes the images appear more stable under different lighting conditions. The proposed chain exploits DoG filtering as a bandpass filter to reduce the illumination variation effects and noises, and then exploits the gradient domain as an illumination insensitive measure. RSPCA+LDA based on gradient domain provides a robust mechanism to handle occlusions. In addition, it has shown that good performance in the case of the face recognition with single training image per person. Our extensive experimental results on standard face database show that the proposed scheme is very competitive with state-of-the-art methods in terms of accuracy.

References

[1] Braje, W. L. Kersten, D. Tarr, M. J. Troje, N. F. (1998). Illumination effects in face recognition. Psychobiology, 26(4), 371–380.

[2] X. Wei, C.-T. Li, Z. Lei, D. Yi and S. Z. Li, "Dynamic Image-to-Class Warping for Occluded Face Recognition," IEEE Transactions on Information Forensics and Security, vol. 9, no. 12, pp. 2035-2050, Dec 2014.

[3] S. Du and R. Ward. Wavelet-based illumination normalization for face recognition. IEEE International Conference on Image Processing, ICIP 2005. volume 2, pages II – 954–7, sept. 2005.

[4] T. Ahonen, A. Hadid, and M. Pietikainen. Face description with local binary patterns: Application to face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(12):2037 –2041, dec.2006.

[5] A. Georghiades, P. Belhumeur, and D. Kriegman. From few to many: illumination cone models for face recognition under variable lighting and pose. IEEE Transactions on Pattern Analysis and Machine Intelligence,23(6):643 –660, jun 2001.

[6] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210 – 227, Feb. 2009.

[7] A. Martınez and R. Benavente. The ar face database. Computer Vision Center, Technical Report, 24, 1998.

[8] X. Tan, S. Chen, Z.-H. Zhou, and J. Liu. Face recognition under occlusions and variant expressions with partial similarity. IEEE Transactions on Information Forensics and Security, 4(2):217 –230, june 2009.

[9] G. Tzimiropoulos, S. Zafeiriou, and M. Pantic, "Subspace learning from image gradient orientations," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 12, pp. 2454 – 2466, 2012.

[10] Zhang, T.P., Tang, Y.Y., Fang, B., Shang, Z.W., Liu, X.Y., "Face recognition under varying illumination using gradientfaces," IEEE Transactions on Image Processing, 18 (11): 2599-2606, 2009.

[11] Meng, D., Zhao, Q. and Xu, Z. "Improve robustness of sparse PCA by L1-norm maximization". Pattern Recognition 45:487-497, 2012.

[12] P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, Eigenfaces vs. fisherfaces: recognition using class specific linear projection, IEEE Transactions on Pattern Analysis and Machine Intelligence 19 (1997) 711–720.

[13] V. Todorov and P. Filzmoser. Comparing classical and robust sparse PCA. Advances in Intelligent Systems and Computing, 190 AISC, 283-291, 2013.

[14] A. M. Martınez, "Recognizing imprecisely localized, partially occluded, and expression variant faces from a single sample per class," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 6, pp. 748 – 763, 2002.

[15] K. Lee, J. Ho, and D. Kriegman, "Acquiring linear subspaces for face recognition under variable lighting," IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 27, no. 5, pp. 684–698, 2005.

[16] Kanan, H.R., Faez, K., Gao, Y.: Face recognition using adaptively weighted patch pzm array from a single exemplar image per person. Pattern Recognition 41(12), 3799–3812 (2008).

[17] L. Zhang, M. Yang, X. Feng. Sparse representation or collaborative representation: Which helps face recognition? In ICCV, 2011.

[18] M. Yang and L. Zhang, "Gabor Feature based Sparse Representation for Face Recognition with Gabor Occlusion Dictionary," Proc. European Conf. Computer Vision, 2010.

[19] M. Yang, L. Zhang, J. Yang, D. Zhang. Robust sparse coding for face recognition. In CVPR, 2011.

[20] X. Wei, C.-T. Li, and Y. Hu. Robust face recognition under varying illumination and occlusion considering structured sparsity. In International Conference on Digital Image Computing Techniques and Applications (DICTA 2012), 2012.

[21] X. Tan, S. Chen, Z.-H. Zhou, and F. Zhang, "Recognizing partially occluded, expression variant faces from single training image per person with SOM and soft k-NN ensemble," IEEE Transactions on Neural Networks, vol. 16, no. 4, pp. 875 –886, 2005.

[22] Y. Liu, F. Wu, Z. Zhang, Y. Zhuang, and S. Yan. Sparse representation using nonnegative curds and whey. In CVPR, 2010.

[23] Y. Tang, R. Salakhutdinov, and G. Hinton. Robust boltzmann machines for recognition and denoising. In CVPR, 2012.

[24] K. Jia, T.-H. Chan, and Y. Ma. Robust and practical face recognition via structured sparsity. In ECCV. 2012.

[25] R.Weng, J. Lu, J. Hu, G. Yang, and Y.-P. Tan, "Robust feature set matching for partial face recognition," in IEEE International Conference Computer Vision (ICCV), Dec. 2013, pp. 601 – 608.

[26] X. Tan, B. Triggs, "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions", IEEE Trans Image Process. 2010 Jun;19(6):1635-50.

[27] M. Kamachi, M. Lyons and J. Gyoba, The Japanese Female Facial Expression (JAFFE) Database, http://www.kasrl.org/jaffe.html.

[28] A. Nefian and I. Hayes, M.H., "Hidden markov models for face recognition," in IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), vol. 5, May 1998, pp. 2721 – 2724.

[29] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," ACM Transactions on Intelligent Systems and Technology, vol. 2, pp. 27:1 – 27:27, 2011, http://www.csie.ntu.edu.tw/~cjlin/libsvm.

[30] J. Yang, J.Y. Yang, "Why can LDA be performed in PCA transformed space?" Pattern Recognition, 2003, 36(2), pp. 563-566.

[31] X. Zhuang and D. Dai, "Improved Discriminant Analysis for High Dimensional Data and Its Application to Face Recognition," Pattern Recognition, vol. 40, 2007, pp. 1570–1578.

[32] W.M. Zuo, D. Zhang, J. Yang, K.Q. Wang, BDPCA plus LDA: a novel fast feature extraction technique for face recognition, IEEE Transactions on Systems, Man, and Cybernetics—Part B 36 (4) (2006) 946–953.

Author Biography

Huda M.S. Algharib received her BS in computer science from the University of Benghazi (2008) and her MS in computer engineering from Yildirim Beyazit University (2017). She is currently working towards her PhD degree in Computer Science and Engineering. Her research interests include computer vision, image processing, pattern recognition, and machine learning.

Osman Serdar Gedik received his BS, MS, and Ph.D. degrees in Electrical and Electronics Engineering from the University of Middle East Technical, in (2006), (2008), and (2014), respectively. His work has focused on the Human-computer Interaction, Computer Graphics, Computer vision, image processing, pattern recognition, and machine learning.