Illumination-Robust Local Pattern Descriptor for Face Recognition

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Abstract. In this paper, we propose a simple descriptor called an extended center-symmetric pattern (ECSP) for illumination-robust face recognition. The ECSP operator encodes the texture information of a local face region by emphasizing diagonal components of a previous center-symmetric local binary pattern (CS-LBP). Here, the diagonal components are emphasized because facial textures along the diagonal direction contain much more information than those of other directions. The facial texture information of the ECSP operator is then used as the input image of an image covariance-based feature extraction algorithm. Performance evaluation of the proposed approach was carried out using various binary pattern operators and recognition algorithms on the extended Yale B database. The experimental results demonstrated that the proposed approach achieved better recognition accuracy than other approaches, and we confirmed that the proposed approach is effective against illumination variation.

Keywords: LBP, ECSP, Face Recognition.

1 Introduction

Face recognition has become one of the most popular research areas in the fields of image processing, pattern recognition, computer vision, and machine learning, because it spans numerous applications. However, illumination variation that occurs on face images drastically degrades the recognition accuracy [1]. To overcome the problem caused by illumination variation on face images, local texture descriptors such as local binary pattern (LBP) [2], centralized binary pattern (CBP) [3], and center-symmetric local binary pattern (CS-LBP) [4], have recently received increasing interest due to their illumination-robust characteristic. The LBP is a non-parametric kernel which summarizes the local spatial structure of an image. Moreover, it has important properties of robustness against monotonic illumination changes and computational simplicity. Recently, the CBP and CS-LBP were also introduced for face representation. Compared to the LBP, the CBP and CS-LBP produce fewer binary units, so they have the advantage that they can reduce the vector length of corresponding histogram feature. Based on these previous works, this paper introduces a texture descriptor constructed with the proposed extended center-symmetric pattern (ECSP) for illumination-robust face recognition. Unlike previous local texture descriptors that assign a binary code by labelling the pixels toward continuous directions, the proposed ECSP

H.-Y. Jeong et al. (eds.), *Advances in Computer Science and Its Applications*, Lecture Notes in Electrical Engineering 279,
DOI: 10.1007/978-3-642-41674-3_28,

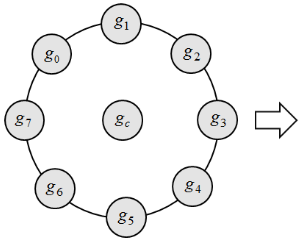
operator encodes the facial textures by reordering the bit priorities as pre-defined directions. Furthermore, this paper proposes a new face recognition approach that directly utilizes a face image transformed by the ECSP descriptor as the input for the image covariance-based feature extraction algorithm, such as two-dimensional principal component analysis (2D-PCA) [5]. This is a new approach compared to most previous research, because previous works utilized the binary pattern descriptors for histogram feature extraction of the face image [2-4]. The proposed approach has the advantages that the illumination effects can be degraded by using the ECSP descriptor and 2D-PCA is more robust against illumination variation than global features such as principal component analysis (PCA) [6], since 2D-PCA is a line-based local feature.

2 Methodology

The LBP was originally proposed for texture description, and it has been widely exploited in many applications such as video retrieval, aerial image analysis, and visual inspection. Recently, the LBP has been extensively exploited for facial image analysis, including face detection, face recognition, facial expression analysis, gender/age classification, and so on. The LBP operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the center value, and considering the results as a binary number, of which the corresponding decimal number is used for labelling [2]. The LBP code is derived by

$$LBP(P,R) = \sum_{p=0}^{P} s(g_p - g_c)\times 2^p , \quad s(x)=\begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} , \tag{1}$$

where g_c and g_p denote the center pixel value and neighborhood pixel values, respectively; P means the number of neighbors; and R means the radius of the neighborhood. The LBP-based approaches are attracting much attention from researchers due to their advantages of simple computation, robustness to illumination variation, and discriminative ability. However, the LBP operator has several disadvantages: (1) they produce rather long histograms, which affect the recognition speed, especially on large-scale database; (2) under certain circumstance, they miss the local structure as they do not consider the effect of the center pixel; and (3) the binary data produced by them are sensitive to noise [3][4]. Thus, the CBP and CS-LBP have been proposed for face representation more recently. The CBP operator compares pairs of neighbors which are within the same diameter, and compares the central pixel with the mean of all the pixels as shown in Fig. 1. The CS-LBP operator can be also computed by only considering the corresponding patterns of symmetric pixels as shown in Fig. 1. In these methods, instead of comparing the grey level value of each pixel with the center pixel, the center-symmetric pairs of pixels are compared. In addition, they are closely related to the gradient operator. They consider the grey level differences between pairs of opposite pixels in a neighborhood. Thus, they take advantage of both LBP and gradient-based features, and they reduce the computational complexity in comparison with basic LBP.



$$CBP(P,R) = \sum_{p=0}^{(P/2)-1} s(g_p - g_{p+(P/2)}) \times 2^p + s(g_c - (\sum_{p=0}^{P-1} g_p + g_c)/(P+1)) \times 2^{P/2},$$

$$CS\text{-}LBP(P,R) = \sum_{p=0}^{(P/2)-1} s(g_p - g_{p+(P/2)}) \times 2^p,$$

$$where,\ s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Fig. 1. CBP and CS-LBP operators

To make a more significant pattern against illumination variation, we modified the CS-LBP operator by reordering the bit priorities as pre-defined directions. Generally, the decimal value of most binary pattern operators is created by combining each binary code toward continuous direction. In this view, we can suppose that each binary unit has a different characteristic in terms of facial texture. In other words, previous binary pattern operators have not considered the relation between each bit position and facial texture. Thus, we first investigated their corresponding relation by composing a texture image, in which each texture image is created using only one pair of symmetric pixels. The resultant texture images are shown in Fig. 2, while P and R are 8 and 1, respectively. As seen in Fig. 2, the composed texture image (see Fig. 2 (e)) using only horizontal pixels contains more indistinguishable texture than other composed images (see Fig. 2 (b), (c), and (d)). This component has negative effects on the complete binary pattern image of the CS-LBP. Thus, we assign low priority to component of the horizontal directions. In addition, notice that other composed images have similar textures as seen in Fig. 2 (b), (c), and (d).

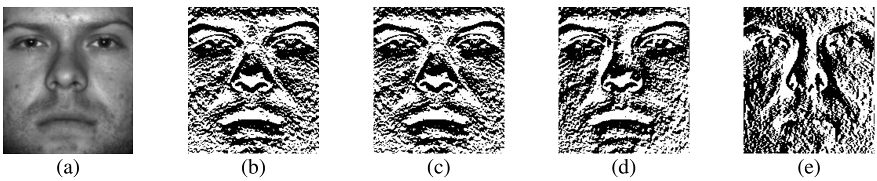


Fig. 2. Relation of bit position and facial texture; (a) Original image, (b) Composed image using only g_0 and g_4 terms, (c) Composed image using only g_1 and g_5 terms, (d) Composed image using only g_2 and g_6 terms, (e) Composed image using only g_3 and g_7 terms

Due to the lack of significant facial textures in the composed image using only horizontal pixels, we rearrange the bit priorities in time of pattern generation as follows:

$$ECSP(P,R) = \sum_{p=0}^{(P/2)-1} s(g_p - g_{p+(P/2)}) \times 2^{w_{P,R}(p)}, \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}, \tag{2}$$

where $w_{P,R}(p)$ means a weighting function to decide the bit priority. Here, suppose that the 3x3 neighborhood pixel positions are set as shown in Fig. 1. When P and R are set 8 and 1, respectively, $w_{8,1}(p)$ for ECSP(8, 1) is defined by

$$w_{8,1}(p)=(3,1,2,0),\ \ p=0,1,2,3. \tag{3}$$

Furthermore, let us suppose that the pixels of an extended 5x5 neighborhood are situated like those of the 3x3 image patch. Then, $w_{16,2}(p)$ for ECSP(16, 2) is defined by

$$w_{16,2}(p)=(7,5,1,3,6,2,0,4),\ \ p=0,1,2,3,4,5,6,7. \tag{4}$$

In the proposed ECSP operator, we assign the high weight to components of diagonal directions, and we then assign following weight to components of the vertical and horizontal directions as sequential steps. In addition, we expand the image patch to 5x5 pixel sizes to obtain a more illumination-robust facial texture, leading to performance improvement as seen in the experimental results. Fig. 3 shows facial texture images transformed by various binary pattern operators, such as LBP, CBP, CS-LBP, ECSP(8, 1), and ECSP(16, 2). As seen Fig. 3, we can confirm that the ECSP operator achieves a more significant facial texture than other operators, since we assign the lowest bit priority to component of the horizontal direction. Moreover, the ECSP(16, 2) image is clearer than the ECSP(8, 1) image as shown in Fig. 3 (e) and (f) in terms of impulse-like noises. Consequently, the proposed ECSP operator seems more stable than other binary pattern images, as shown in Fig. 3, since it has fewer noise components than other images.

Raw LBP(8, 1) CBP(8, 1) CS-LBP(8, 1) ECSP(8, 1) ECSP(16, 2)

Fig. 3. Example of various binary pattern images

3 Experiments

The performance evaluation was carried out using well-known recognition approaches, namely, PCA [6], 2D-PCA [5] and Gabor-wavelets based on LBP [2] on the Yale B database. Note that this work utilized face images transformed by the ECSP descriptor as the input for an image covariance-based feature extraction algorithm, such as 2D-PCA, unlike previous studies. In the Yale B database, we employed 2,414 face images for 38 subjects representing 64 illumination conditions in the frontal pose, in which the subjects comprised 10 individuals in the original Yale B database and 28 individuals in the extended Yale B database. Also, we partitioned the face database into training and testing sets. Generally, the Yale B database can be subdivided into several subsets depending on the direction of light [7], so we employed several images from various subsets for training, and images from the remaining subsets were used for testing. As a result, the recognition results in relation to the various training sets are shown in Table 1. For the Yale B database, the recognition accuracies of the proposed method using ECSP(16, 2) and 2D-PCA were 95.58%, 96.18%, 97.99%, 98.28% and 98.48%, when the training sets were ‘subset 1’, ‘subset 2’, ‘subset 3’, ‘subset 4’, and ‘subset 5’, respectively. These results demonstrate that the proposed method achieved the best recognition accuracies in most cases. In addition, the proposed method showed performance improvements of 26.08%, 23.07%, 11.20%, 32.44%, and 33.69% over the Gabor-wavelets approach based on LBP when training sets were ‘subset 1’, ‘subset 2’, ‘subset 3’, ‘subset 4’, and ‘subset 5’, respectively. In particular, the recognition results using ECSP images showed significant performance improvements over those of the approaches using CBP and CS-LBP images. Consequently, we experimentally confirmed the robustness and effectiveness of the proposed method under varying lighting conditions.

Table 1. Summary of maximum recognition rates

Recognition Approaches		Training Set				
		Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
PCA	LBP	79.89%	68.32%	79.67%	86.14%	85.67%
	CBP	60.57%	26.16%	43.60%	69.12%	47.66%
	CS-LBP	60.86%	37.15%	68.73%	74.97%	55.73%
	ECSP(8,1)	83.74%	57.02%	93.24%	93.98%	91.64%
	ECSP(16,2)	**92.86%**	**92.52%**	**96.75%**	**97.53%**	**95.85%**
2D-PCA	LBP	89.24%	83.64%	92.67%	91.25%	96.55%
	CBP	73.68%	63.83%	81.53%	92.16%	77.08%
	CS-LBP	74.30%	70.12%	84.57%	91.46%	80.64%
	ECSP(8,1)	94.97%	92.62%	96.49%	97.31%	97.72%
	ECSP(16,2)	**95.58%**	**96.18%**	**97.99%**	**98.28%**	**98.48%**
Gabor-wavelets based on LBP	Raw	57.14%	55.88%	64.75%	48.06%	41.28%
	Histogram	**69.50%**	**73.11%**	**86.79%**	**65.84%**	**64.79%**

4 Conclusion

This paper proposed a novel face recognition approach that integrated the ECSP image and 2D-PCA under illumination-variant conditions. Through experimental results, the proposed approach showed the best recognition accuracy compared to different approaches; thus, we confirmed the effectiveness of the proposed approach.

Acknowledgment. This work was supported by the DGIST R&D Program of the Ministry of Education, Science and Technology of Korea (13-IT-03). It was also supported by Ministry of Culture, Sports and Tourism (MCST) and Korea Creative Content Agency (KOCCA) in the Culture Technology (CT) Research & Development Program (Immersive Game Contents CT Co-Research Center).

References

1. Lian, Z., Er, M.J.: Illumination normalization for face recognition in transformed domain. Electronics Letters 46(15), 1060–1061 (2010)
2. Huang, D., Shan, C., Ardabilian, M., Wang, Y., Chen, L.: Facial image analysis based on local binary patterns - A survey. IEEE Trans. Sys. 41(6), 765–781 (2011)
3. Fu, X., Wei, W.: Centralized binary patterns embedded with image Euclidean distance for facial expression recognition. In: Int. Conf. Neural Computation (2008)
4. Heikkilä, M., Pietikäinen, M., Schmid, C.: Description of interest regions with center-symmetric local binary patterns. In: Kalra, P.K., Peleg, S. (eds.) ICVGIP 2006. LNCS, vol. 4338, pp. 58–69. Springer, Heidelberg (2006)
5. Jian, Y., David, Z., Alejandro, F., Yang, J.Y.: Two-dimensional PCA: A new approach to appearance-based face representation and recognition. IEEE Trans. Pattern Anal. Mach. Intell. 26(1), 131–137 (2004)
6. Turk, M., Pentland, A.: Eigenfaces for recognition. J. Cogn. Neurosci. 3(1), 71–86 (1991)
7. Georghiades, A., Belhumeur, P., Kriegman, D.: From few to many: Illumination cone models for face recognition under variable lighting and pose. IEEE Trans. Pattern Anal. Mach. Intell. 23(6), 643–660 (2001)