Face Recognition Based on Local Directional Pattern Variance (LDPv)

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Abstract. Face recognition is becoming very popular tools for a successful human commuter interaction system. It seems to be a good compromise between reliability and social acceptance and balances security and privacy well. In this paper, we have presented a new appearance-based feature descriptor, the local directional pattern Variance (LDPv), to represent facial components and analyzed its performance for face. A LDP feature is computed from the relative edge response values in all eight directions at each pixel position, and then, the LDPv descriptor of a facial image is generated from the integral projection of each LDP code weighted by its corresponding variance. The final face representation is then described by the concatenated histogram of LDPv of local regions that encodes both global and local texture information. The recognition performance with FERET datasets demonstrates the robustness of proposed LDPv descriptor for representing appearance of facial image over other existing state of the art approaches.

Keywords: Facial image representation, face recognition, local transitional pattern, contrast Features extraction.

1 Introduction

In recent time automatic face recognition (AFR) gained an escalating interest in building natural human computer interaction systems. As AFR system becomes an extensively explored area of research, clearly defined recognition system steps is already been established which are: detection, or finding where the faces are in an image; alignment ensuring the detected face(s) line up with a target face or a model; representation or feature description transforms the aligned faces into some representation emphasizing certain facial aspects; and classification, which determines whether a certain face matches a target face [1]. In this work, we mainly provide a robust representations scheme compare to other state-of-the-art facial image representation.

In literature, we found two types of face representation techniques: subspace based holistic feature and local appearance feature. Principal component analysis (PCA) which is particularly known as eigenface [2] is one of the initial subspace based method applied in AFR. Recently some other global features like independent component analysis (ICA) [3], gradientface [4] etc. showed promising result in image representation for AFR; however all of these representations suffer during illumination variation and alignment error.

One of the most successful local face appearance representations are Gabor features. A spatial histogram model local binary patterns (LBP) has also been proposed to represent visual objects, and successfully applied for different application in facial image analysis [5] like human detection, face recognition or expression recognition. LBP is basically a fine-scale descriptor that captures small texture details, in contrast to Gabor features which encode facial shape and appearance over a range of scales. Using LBP, Ahonen et al. [6] have reported impressive results on the FERET database. Nevertheless LBP considers only first order intensity pattern change in a local neighborhood which fails to extract detailed information especially during changes in face image due to non-monotonic illumination variation, random noise, and change in age, expression. A more robust facial descriptor, named as Local Directional Pattern (LDP), was devised by Jabid et al. [7], where the LDP representation of face demonstrated better recognition performance than LBP. In this work, we propose the LDP variance (LDPv), which characterizes both spatial structure (LDP) and contrast (variance of local texture) information for more accurate face recognition performance.

2 Local Directional Pattern Variance (LDPv) Descriptor

2.1 LDP

LDP is a gray-scale texture pattern which characterizes the spatial structure of a local image texture. A LDP operator computes the edge response values in all eight directions at each pixel position and generates a code from the relative strength magnitude. Since the edge responses are more illumination and noise insensitive than intensity values, the resultant LDP feature describes the local primitives including different types of curves, corners, junctions; more stably and retains more information. Given a central pixel in the image, the eight directional edge response values $\{m_i\}$, $i = 0,1,...,7$ are computed by Kirsch masks M_i in eight different orientations centered on its position. The masks are shown in fig. 1.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East M_0 North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

Fig. 2. Kirsch edge masks in all eight directions.

These eight edge responses magnitude are utilized to generate an eight bit binary number which can describe the local edge pattern of a particular pixel. Different edge responses and the corresponding bit position is shown with the following figure.

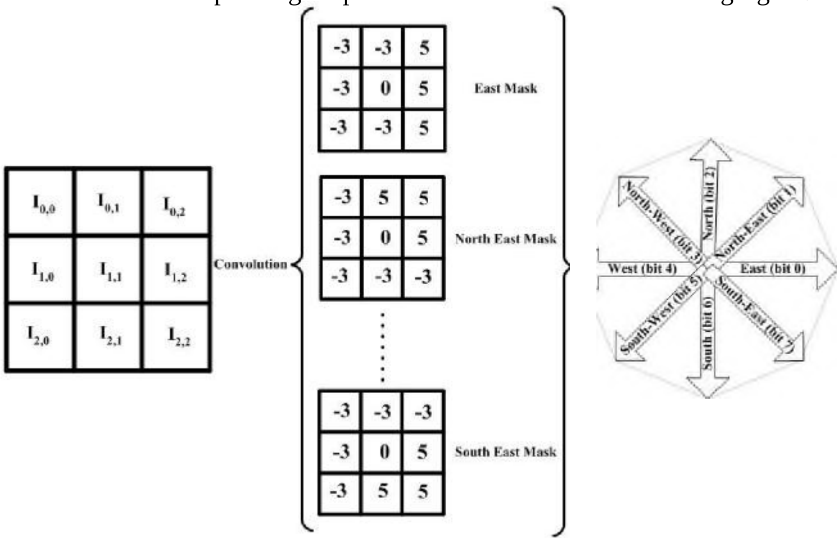

Fig. 2. LDP binary bit positions.

The response values are not equally important in all directions. The presence of corner or edge show high response values in some particular directions. Therefore, we are interested to know the k most prominent directions in order to generate the LDP. Here, the top k directional bit responses are set to 1. The remaining (8-k) bits of 8-bit LDP pattern is set to 0. Finally, the LDP code is derived which is shown by an exemplary figure with k=3. After computing all the LDP code, the input image of size is represented by a LDP histogram which is LDP descriptor of that image.

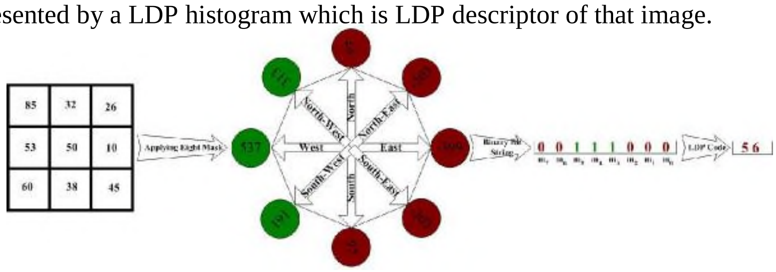

Fig. 3. LDP code with k = 3.

2.2 LDPv Descriptor

Generally, texture can be well represented when characterized by a spatial structure along with its contrast [8]. The LDP feature only contains the distribution of local structures. Here, a low contrast structure equally contributes to the descriptor as a high contrast one. However, texture with significant contrast should impact more since human eyes are more sensitive to high contrast regions. Hence, we like to account the contrast information within the feature descriptor. The variance of a structure is related to the texture feature. Generally, high frequency texture regions have higher variances and contribute more to the discrimination of texture images [9]. Therefore, the variance σ is introduced as an adaptive weight to adjust the contribution of the LDP code in the histogram generation.

$$\sigma(LDP_k(r,c)) = \frac{1}{8}\sum_{i=0}^{7}(m_i - \bar{m})^2 . \qquad (1)$$

where, $\bar{m}$ is the average of all directional responses $\{ m_i \}$ for position (r, c).

LDPv generated from the whole image loses some location information. But for face images, some degree of location and spatial relationship well represent the image content [10]. Hence, the basic histogram is modified to an extended histogram, where the image is divided into g number of regions $R_0, R_{1,\ldots,R_{g-1}}$ (shown in fig. 5), and the $LDPv^i$ histogram is built for each region R_i. Finally, concatenating all the basic $LDPv^i$ distributions yields the descriptor vector of size $g \cdot n$, where n is the size of each basic LDPv histogram. This extended feature vector represents both texture and contrast information with some extent of spatial relationship.

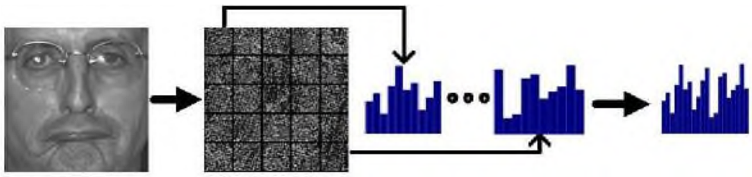

Fig. 4. A face image is divided into small regions from which LDPv histograms are extracted and concatenated into a single LDPv descriptor.

3. Face Recognition

From the pattern classification perspective, a natural problem of face recognition is having a large number of classes but only a few, sometimes only one, number of training sample(s) are available for per class. In this situation, more sophisticated classifier is not applicable rather simple nearest-neighbor classifier is used in classify the face. Several dissimilarity measures have been proposed to compare closeness between two histograms named as – Histogram intersection, Log-likelihood statistics and Chi square statistics (χ^2). The performance of the log-likelihood measure is poor on small windows, and the Chi-square measure performs slightly better than histogram. Consequently, Chi-square statistic is used in this paper.

$$\chi^2(S,M) = \sum_i \frac{(S_i - M_i)^2}{(S_i + M_i)} \qquad (2)$$

where, S is the test sample and M is the template LDPv histogram descriptor. A weighted χ^2 statistics might be used to give more or less importance to particular regions such as eye, nose, and mouth regions.

$$\chi^2_w(S,M)=\sum_{i,j} w_i \frac{\left(S_{i,j}-M_{i,j}\right)^2}{S_{i,j}+M_{i,j}} \quad (3)$$

where indices ***i*** refer to the region number, ***j*** indicates histogram bin number of that region and w_i is the associated weight of region ***i***.

4 Experimental Result

The performance of proposed LDPv pattern is tested in the face recognition problem in with images from the FERET database [11]. Many approaches, such as Principle Component Analysis (PCA), Bayesian approach, Elastic Bunch Graph Match (EBGM) etc. are available for comparisons. LBP-based methods also have been recently proposed and have achieved the state-of-the-art results on the FERET database. Hence in this section we have conducted experiments on FERET face database (with 1196 subjects) and compared with existing methods.

The FERET database consists of a total of 14,051 gray-scale images representing 1,199 individuals. The images contain variations in lighting, facial expressions, aging effects etc. In this work, we assume user supposed to co-operate with the system, however environmental changes may appear a lot. Hence in this work, only frontal faces are considered with different lighting condition, different expression and with aging effects on the face image. These facial images are divided into five sets:

(i) fa set, used as a gallery set, contains frontal images of 1,196 people.
(ii) fb set (1,195 images). The subjects were asked for an alternative facial expression.
(iii) fc set (194 images). The photos were taken under different lighting conditions.
(iv) dupI set (722 images). The photos were taken later in time.
(v) dupII set (234 images). This is a subset of the dup I set containing those images that were taken at least a year after the corresponding gallery image.

Table 1. The recognition result of the LDPv in comparison with other method

Method	fb	fc	dupI	dupII
LDPv, weighted	0.97	0.74	0.64	0.59
LDPv, un-weighted	0.97	0.71	0.60	0.57
LBP	0.97	0.69	0.56	0.54
PCA	0.85	0.65	0.44	0.22
Bayesian	0.82	0.37	0.52	0.32
EBGM	0.90	0.42	0.46	0.24

Images from the FERET database are cropped and normalized to 200×200 pixels based on the ground truth positions of the two eyes and mouth. No further alignment of facial features such as alignment of mouth is performed in our algorithm. We used *fa* image set as gallery image and other four sets (*fb, fc*, *dupI and dupII*) as probe images. One image from probe set is compared using mentioned dissimilarity measure with all the images from gallery image set (*fa* set). The classification result is achieved through the nearest neighbor classification method with facial feature represented by LDPv descriptor. Table 1 shows recognition performance of proposed method along with other methods which ascertain the superiority of our method.

5 Conclusion

In this paper, we have presented a facial expression recognition system based on the proposed LDPv representation, which encodes the spatial structure and contrast information of facial expressions. Extensive experiments illustrate that the LDPv features are effective and efficient for expression recognition. The discriminative power of the LDPv descriptor mainly lies in the integration of local edge response pattern and contrast information that makes it robust and insensitive to noise and non-monotonous illumination changes. Furthermore, with DR functions, like PCA, the newly transformed LDPv features also maintain a high recognition rate with lower computational cost. Once trained, our system can be used in consumer products for human-computer interaction by facial expressions.

References

1. W. Zhao, R. Chellappa, P. J. Phillips, A. Rosenfeld, “Face Recognition: A Literature Survey,” ACM Computing Surveys., vol. 35, no. 4, pp.399-458, Dec. 2003.
2. M. Turk and A. Pentland, “Eigenfaces for Recognition,” Journal of Cognitive Neuroscience, vol. 3, no. 1, pp. 71-86, 1991.
3. P. C. Yuen and J. H. Lai, “Face Representation using Independent Component Analysis,” Pattern Recognition, vol. 35, no. 6, pp. 1247 –1257, Jun. 2002.
4. T. Zhang, Y. Y. Tang, Z. Shang, and X. Liu, 2009, "Face Recognition Under Varying Illumination using Gradientfaces," IEEE Transactions, vol.18, no.11, pp.2599-2606.
5. C. Shan, S. Gong, and P. W. McOwan, “Facial expression recognition based on Local Binary Patterns: A comprehensive study,” Image Vision Comput, vol. 27, pp. 803–816, 2009.
6. T. Ahonen, A. Hadid, and M. Pietikainen, “Face Recognition with Local Binary Patterns,” Proc. European Conerence. Computer Vision (ECCV ‘06), pp. 469–481, 2006.
7. T. Jabid, M. H. Kabir, and O. S. Chae, “Local Directional Pattern (LDP) for Face Recognition,” IEEE International Conference on Consumer Electronics, January 2010.
8. T. Ojala and M. Pietikainen, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Trans. Pattern Anal. Mach., vol. 24, no. 7, pp. 971–987, Jul. 2002.
9. B.S. Manjunath, W.Y. Ma, Texture features for browsing and retrieval of image data, IEEE Trans. Pattern Anal. Mach., vol. 18, no. 8, pp. 837–842, 1999.
10. S. Gundimada and V. K. Asari, “Facial Recognition Using Multisensor Images Based on Localized Kernel Eigen Spaces,” IEEE Trans. on Image Processing, vol. 18, no. 6, pp. 1314 - 1325, 2009.
11. P.J. Phillips, H. Wechsler, J. Huang, and P. Rauss, “The FERET Database and Evaluation Procedure for Face Recognition Algorithms,” Image and Vision Computing, vol. 16, no. 10, pp. 295–306, 1998.