Neurocomputing 119 (2013) 375–384

Contents lists available at SciVerse ScienceDirect

Neurocomputing

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

Face recognition with enhanced local directional patterns

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ARTICLE INFO

Article history:
Received 9 November 2011
Received in revised form
13 November 2012
Accepted 20 March 2013
Communicated by M.S. Bartlett
Available online 6 June 2013

Keywords:
Edge gradient
Kirsch masks
Local directional patterns
Face recognition

ABSTRACT

This paper presents a novel approach based on enhanced local directional patterns (ELDP) to face recognition, which adopts local edge gradient information to represent face images. Specially, each pixel of every facial image sub-block gains eight edge response values by convolving the local 3×3 neighborhood with eight Kirsch masks, respectively. ELDP just utilizes the directions of the most prominent edge response value and the second most prominent one. Then, these two directions are encoded into a double-digit octal number to produce the ELDP codes. The ELDP dominant patterns ($ELDP^d$) are generated by statistical analysis according to the occurrence rates of the ELDP codes in a mass of facial images. Finally, the face descriptor is represented by using the global concatenated histogram based on ELDP or $ELDP^d$ extracted from the face image which is divided into several sub-regions. The performances of several single face descriptors not integrated schemes are evaluated in face recognition under different challenges via several experiments. The experimental results demonstrate that the proposed method is more robust to non-monotonic illumination changes and slight noise without any filter.

1. Introduction

During the past few decades, biometrics have played a very useful role in many fields such as surveillance, human–computer interface, judicature and security identification [1]. Biometrics recognition is an automatic method of recognizing individuals by means of comparing feature vectors derived from their physiological or/and behavioral characteristics. The common physiological characteristics include face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear, voice and so on [2]. Facial images can be easily acquired from a distance by a few inexpensive fixed cameras without the user's active participation or any health risks [3]. Hence, face recognition systems are more easily accepted by users and have been receiving researchers' significant attentions.

Face description method is the key technology of face recognition systems. Up to the present, there are many face representation approaches including principal component analysis (PCA) [4], independent component analysis (ICA) [5], linear discriminant analysis (LDA) [6], 2DPCA [7], $(2D)^2$PCA [8], LLE [9], LPP [10], NPE [11], VDE [12], MMNPE [13], DWDPA [14,15], Gabor Face [16], local binary patterns (LBP) [17], LGBP [18], CS-LBP [19], GV-LBP [20], local directional pattern (LDP) [21], etc. Among them, PCA, 2DPCA, $(2D)^2$PCA, LDA, LLE, LPP, NPE, VDE, MMNPE and DWDPA are the typical methods of extracting holistic features. On the other hand, LBP, CS-LBP, LGBP, GV-LBP and LDP aim to make full use of local appearance features. The kind of local descriptors have gained much attention because of their robustness to challenges such as expression, pose and illumination variations. Generally, the holistic approaches are sensitive to complicated changes including the aforementioned changes. In addition, the recognition accuracy of the holistic approaches is inferior to that of the local descriptor approaches [17,20,21].

Recently, LBP has gained more attentions due to its simplicity and excellent performance in face recognition and texture analysis. The original LBP operator is an effective texture descriptor with LBP codes that encode the local 3×3 neighborhood structure around each pixel with the center. Every pixel gets a binary number by thresholding its 8-neighbor gray values with its center value. Due to its flexibility, the LBP method can be easily modified to make it suitable for the needs of different types of problems. Therefore, several extensions and modifications of LBP have been proposed and can be learned in the literature [22]. To capture the texture at different scales, the original LBP operator was later extended to $LBP^{u2}_{P,R}$ [23] operator where the notation (P, R) denotes P sampling points on a circle radius of R and $u2$ denotes the operator that stands for using uniform patterns and uniting all remaining patterns to a single pattern. LBP operator is robust to

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http://dx.doi.org/10.1016/j.neucom.2013.03.020

monotonic illumination variation, but it is sensitive to non-monotonic illumination change and random noise. Jabid et al. [24] proposed a more robust facial feature based on local directional patterns (LDP). The LDP descriptor considers the edge response values derived from the Kirsch gradient operator in eight directions around a pixel instead of pixel intensities like LBP. Because edge gradient is more stable than the pixel intensity, LDP feature provides more consistency in the presence of noise. The original LDP codes are generated by setting the k most prominent directional bits to 1, but this method ignores the distinction between the most prominent edge response direction and the second most prominent one. However, this distinction is very important for reliable face representation and is effectively utilized in the enhanced local directional patterns (ELDP) proposed in this work.

The remainder of this paper is organized as follows. Section 2 presents the ELDP method for face recognition, Section 3 compares the recognition performances of several single face descriptors including our methods without any intentional noise, Section 4 provides the experimental results when the face images are contaminated by slight random Gaussian white noise, and Section 5 concludes our work and discusses the future work simply.

2. Enhanced local directional patterns (ELDP)

After briefly reviewing the local directional patterns, this section introduces the ELDP and describes its relation to LBP. Then, the stability and reliability of ELDP are discussed and the ELDP dominant patterns (ELDP^d) are acquired via general statistical analysis according to the occurrence rates of ELDP codes in a mass of facial images from several face databases. Finally, we give the procedure of face representation and recognition using ELDP or ELDP^d.

2.1. Local directional patterns (LDP)

The local directional pattern of each pixel is an eight-bit binary code calculated by comparing the edge response values of different directions in local 3×3 neighborhood. For this purpose, we convolve the 3×3 neighborhood with eight Kirsch masks [25] to get the directional edge response values ($m_0 \ldots m_7$) respectively. Kirsch masks are shown in the Fig. 1.

Then the top k response values $|m_i|$ ($i=0\ldots7$) are selected and the corresponding directional bits are set to 1. The remaining (8-k) bits are set to 0, thus we get the binary expression of a local directional pattern. Finally, the binary number is converted into a decimal number. The whole procedure is shown in Fig. 2. Fig. 3 shows an example of $k=3$.

$$M_0 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad M_1 = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad M_2 = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad M_3 = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$M_4 = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad M_5 = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad M_6 = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad M_7 = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

Fig. 1. Kirsch templates in eight directions.

$$\begin{bmatrix} G3 & G2 & G1 \\ G4 & G(i,j) & G0 \\ G5 & G6 & G7 \end{bmatrix} \xrightarrow{*\{M_i\}} \begin{bmatrix} |m_3| & |m_2| & |m_2| \\ |m_1| & x & |m_0| \\ |m_4| & |m_6| & |m_7| \end{bmatrix} \xrightarrow{|m_k|} \begin{bmatrix} b3 & b2 & b1 \\ b4 & x & b0 \\ b5 & b6 & b7 \end{bmatrix}$$

Fig. 2. The procedure of calculating LDP code.

$$\begin{bmatrix} 38 & 39 & 101 \\ 33 & 67 & 109 \\ 56 & 111 & 117 \end{bmatrix} \xrightarrow{*\{M_i\}} \begin{bmatrix} 932 & 388 & 180 \\ 796 & x & 804 \\ 212 & 460 & 884 \end{bmatrix} \xrightarrow{|m_k|} \begin{bmatrix} 1 & 0 & 0 \\ 0 & x & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

LDP Binary Code=10001001
LDP Decimal Code=137

Fig. 3. An example of calculating LDP code when $k=3$.

$$\begin{bmatrix} 38 & 39 & 101 \\ 33 & 67 & 109 \\ 56 & 111 & 117 \end{bmatrix} \xrightarrow{*\{M_i\}} \begin{bmatrix} -932 & -388 & 180 \\ -796 & x & \mathbf{804} \\ -212 & 460 & \mathbf{884} \end{bmatrix} \quad \begin{bmatrix} m_3 & m_2 & m_1 \\ m_4 & x & m_0 \\ m_5 & m_6 & m_7 \end{bmatrix}$$

ELDP Octal Code=$(70)_8$
ELDP Decimal Code=56

Fig. 4. An example of getting the ELDP code.

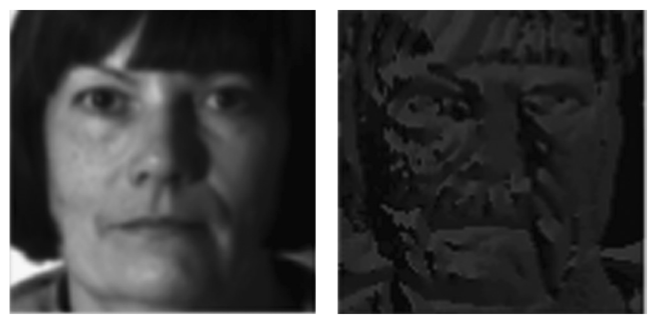

Fig. 5. A face image and its ELDP map.

2.2. ELDP code

According to Fig. 2, LDP is encoded using the absolute values of the convolving results. However, the sign of the original convolving values means two opposite trends (ascending or descending) of the gradient and may contain some more information. Therefore, the enhanced local directional patterns utilize the directions of the most prominent edge response value and the second most prominent one after eight edge response values $\{m_i\}$ ($i=0\ldots7$) come into being. We use the index i of m_i as the representation of the direction of m_i. Thus, eight gradient directions just can be represented by eight octal codes, respectively. Therefore, the ELDP code is formed using a double-digit octal number $(ab)_8$ which can be converted into a decimal number as

$$\text{ELDP Decimal code} = a \times 8^1 + b \times 8^0 \tag{1}$$

where a is the index of the most response value m_a and b is the index of the second most response value m_b. Thus there are totally $A_8^2 = 8 \times 7 = 56$ different ELDP codes. Fig. 4 shows an example of getting the ELDP code. When all pixels of an image are computed into ELDP codes, the image can be expressed by its corresponding ELDP map. Fig. 5 shows the ELDP face map of a facial image from YALE database [26].

2.3. Relation to LBP

In [27], a new framework is given to look at texture descriptors. This framework views the LBP operator as a special filter-based texture