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Dimensionality reduced local directional pattern (DR-LDP) for face recognition

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ABSTRACT

Local Directional Pattern (LDP) is a descriptor used for face recognition. It assigns a code for each pixel in the image, and the resultant LDP-encoded image is divided into regions for which each a histogram is generated. The histogram bins of all the regions are concatenated to form the final descriptor. In contrast to LDP, a dimensionality reduced local directional pattern (DR-LDP) is proposed in this paper. The proposed descriptor computes single code for each block by X-ORing the LDP codes obtained in a single block. During the process, restructuring of the patterns is done by slightly modifying the LDP coding pattern constraints. The significance of DR-LDP is the compact code generation for efficient face recognition. The experiments were carried out on standard databases like FERET, extended YALE-B database and ORL. The resultant DR-LDP descriptor provided better recognition rates, outperforming the existing local descriptor-based methods and proving its efficacy. The compact code can be further extended to provide biometric security.

1. Introduction

Biometrics research is active due to a need for the development of highly secure systems that are invulnerable to attacks. Although many biometric modes exist like the iris, face, hand geometry, voice, the face is more prominently used due to its versatile characteristics that machines can use to simulate human identification of a person (Phillips et al., 2007). Face recognition is still a challenging problem. Humans recognize faces with ease in any complex environment. Face recognition finds applications in surveillance, biometric authentication, human computer interaction, forensics etc. (Guan, Wang, Chen, Bu, & Chen, 2010). Representation of the face is a key step in face recognition (Zhao, Chellappa, Phillips, & Rosenfeld, 2003).

Despite the availability of several face recognition systems, face recognition is still an active area of research in biometrics because the existing systems fail to recognize faces under challenging conditions like different poses, different expressions, and different illumination conditions etc. In the recent past, focus is made on descriptor-based face recognition (Chellappa, Wilson, & Sirohey, 1995) to overcome these challenges.

Face recognition methods are broadly categorized into two types – geometry based feature methods and appearance based feature methods. Geometry-based features utilize global information, which is represented by features, whereas appearance-based features describe the texture of the face. Geometric-based approaches provide better results even with images that contain marginal information. In these approaches, facial features are represented as feature vectors that are associated with face details such as eyes, nose and mouth.

Feature-based face recognition can be employed for face recognition in general and expression identification, aging determination etc. in specific. Geometric shape-based features and appearance-based features are the predominantly used features in descriptor-based face recognition techniques (Tian, Kanade, & Cohn, 2005). Extraction of geometric shape-based features is a cumbersome process since it involves accurate and reliable detection mechanisms (Ramirez Rivera, Rojas Castillo, & Chae, 2013). These features give promising results in a restricted environment (Tian, 2004). The approaches used for feature extraction are Principal

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component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent component Analysis (ICA), Elastic Bunch Graph Matching (EBGM), Local Binary Pattern (LBP), Local Phase Quantization (LPQ), Local Ternary Pattern (LTP), Local Directional Pattern (LDP), Local Derivative Pattern (LDeP), Local Directional Number Pattern (LDN) and Local Directional Number with Gaussian Mask (LDNG).

Sirovich and Kirby (1987) proposed a dimensionality reduced method — principal component analysis (PCA). PCA represents the face patterns in Eigen picture coordinate space. The resultant Eigen face represents the feature space by determining the Eigen vectors associated with the Eigen values for face recognition (Turk & Pentland, 1991). Although the Eigen face reduces the dimensions of the original image drastically, it exhibits fair robustness with different orientations and lighting conditions.

Belhumeur, Hespanha, and Kriegman (1996, 1997) argued that by projecting the feature vector such that LDA maximizes across the scattered points whereas PCA retains the unwanted variations occurred due to lighting and facial expressions. Fisher proposed linear discriminant analysis (LDA), which maximizes between-class variance and minimizes within-class variance to improve the recognition rate irrespective of illumination and pose variation. LDA is used comprehensively in pattern recognition and machine learning (Scholkopft & Mullert, 1999) as well as face recognition (Etemad & Chellappa, 1997). Since it characterizes two or more classes of objects' features, it is called a linear classifier. Like PCA, LDA is a holistic feature based method.

Ojala, Pietikäinen, and Harwood, (1996) introduced local binary patterns (LBP) as a powerful descriptor for describing textural patterns. LBP labels each pixel in a sub-image of 3 × 3 image with the element in the center acting as a threshold. The eight neighbors are compared with the center pixel and each pixel is coded as 1 if greater than or equal to 0, and 0 otherwise. The drawback of LBP descriptor is that it is noise prone.

Ojala, Pietikäinen, and Mäenpää (2002) further extended the LBP operator for use with neighborhoods of different sizes. Circular neighborhoods with bi-linear interpolation techniques are employed here. The multi-resolution based LBP operator is defined in Eq. (1).

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

where P represents the number of sampling points on a circle of radius R. The regularly used LBP is $LBP_{8,2}$.

Another variation of LBP is called uniform LBP. Uniform LBP is an LBP pattern with only two transitions from 0 to 1 or vice-verse. Ahonen, Hadid, and Pietikäinen (2004); Ahonen, Hadid, and Pietikainen (2006) applied LBP to face recognition. They divided the image into regions and LBP was extracted for each region. All the patterns were concatenated as a single pattern that represented the texture of the image. A weighted Chi-square distance metric was employed as a dissimilarity measure between two face images. In feature-based methods, LBP has transformed the dimensions of face recognition research. Ahonen, Rahtu, Ojansivu, and Heikkilä (2008) proposed a similar descriptor named Local Phase Quantization (LPQ), which outperforms LBP and also detects faces in blurred images. Liao, Zhu, Lei, Zhang, and Li (2007) proposed a multi-block LBP (MB-LBP) that encodes both the micro- and macro- structures of image patterns.

Tan and Triggs (2007) proposed a generalized LBP called local ternary pattern descriptor (LTP) for the extraction of textural features. LTP is the result of extending LBP to three codes. It is defined in Eq. (2).

$$s'(u, i_c, t) = \begin{cases} 1 & u \geq i_c + t \\ 0 & |u - i_c| < t \\ -1 & u \leq i_c - t \end{cases} \tag{2}$$

The parameter t in Eq. (2) is the threshold, and is set to 5. Besides LTP, local directional patterns (LDP) and local derivative patterns (LD_eP) have been proposed. Zhang, Gao, Zhao, and Liu (2010) proposed a local derivative pattern to overcome the pitfalls of LBP, while LD_eP explores the directional information of neighborhoods rather than their intensity values.

Jabid, Kabir, and Chae (2010d) have introduced a local feature descriptor LDP for face recognition. It is discussed in detail in Section 2. Jabid et al. have used LDP for gender classification (Jabid, Kabir, & Chae, 2010b), for facial expression identification (Jabid, Kabir, & Chae, 2010a; 2010e) and for object recognition (Jabid, Kabir, & Chae, 2010c). Ramirez Rivera et al. (2013) have proposed a Local Gaussian directional pattern (LGDP) for face recognition. In this paper, instead of using Kirsch masks, the authors have employed the Gaussian masks generated for each direction. The Gaussian mask defined by the authors is given in Eq. (3).

$$M_\sigma(x, y) = G'_\sigma(x + k, y) * G_\sigma(x, y) \tag{3}$$

where k is the offset of the Gaussian wrt x, $*$ is the convolution operator and G is the Gaussian function defined in Eq. (4).

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{4}$$

Local Directional Number pattern (LDN) is another variation of LDP proposed in Ramirez Rivera et al. (2013). LDN works along the same lines as LDP using Krisch masks. The coding is defined in Eq. (5).

$$LDN(x, y) = 8i_{x,y} + j_{x,y} \tag{5}$$

where (x, y) represents the coordinates of the center pixel being coded, $i_{x,y}$ is the direction number of the maximum positive response and $j_{x,y}$ is the directional number of the minimum negative response. The authors have further tried the LDN approach by using Gaussian mask defined in Eq. (3) instead of Kirsch masks. The LDN pattern with the Gaussian mask is labeled as local directional number pattern with Gaussian function (LDNG). LDNG has a greater facial recognition accuracy than LDN.

Generally, there are a number of local descriptors aimed at face recognition. All of them define a mask, superimpose it with the image and calculate the code pattern for the center pixel that coincides with the center of the mask. Motivated by this, this paper proposes a dimensionality reduced LDP for face recognition, where the image is divided into regions, and for each region, an LDP code is generated to keep the originality of the LDP working mechanism at places when deviated. The proposed mechanism is explained in detail in Section 3.

The rest of the paper is organized as follows. Local directional pattern, which form the backbone of the proposed work, is discussed in Section 2. The proposed DR-LDP is discussed in detail in Section 3, experimental results and performance analysis are described in Section 4 and Section 6 concludes the work.

2. Local directional patterns

For each pixel in the image, LDP computes an eight bit binary code. The eight bit pattern is calculated by convolving the local region of the image of size 3 × 3 with Kirsch masks in eight directions. The Kirsch masks are defined in Fig. 1.

For each 3 × 3 region, convolution of the Kirsch masks is done wrt eight directions of the center pixel. For the eight masks defined in Fig. 1, eight responses are obtained labeled as $m_o, m_1, \ldots, m_7$. From these responses, top k responses are selected and set to 1 while the rest of the responses are set to 0. It is defined mathematically in Eq. (6).

$$C[f(x, y)] := (c_i = 1) \quad \text{if } 0 \leq i \leq 7 \text{ and } m_i \geq \psi \tag{6}$$