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Discriminative histograms of local dominant orientation (D-HLDO) for biometric image feature extraction

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ABSTRACT

This paper presents a simple and robust method, namely discriminative histograms of local dominant orientation (D-HLDO), for biometric image feature extraction. In D-HLDO, the local dominant orientation map and the corresponding relative energy map are obtained by applying the singular value decomposition (SVD) to the collected gradient vectors over a local patch. The dominant orientation map and the relative energy map are then used to construct the concatenated histogram features. Local mean based nearest neighbor discriminant analysis (LM-NNDA) is finally employed to reduce the redundancy information and get the low-dimensional and discriminative features. The proposed method is applied to face, finger-knuckle-print and Palm biometrics and is examined using the AR, CMU PIE and FRGCv2.0 face image databases, the PolyU Palmprint database, and the PolyU Finger-Knuckle-Print database. Experimental results demonstrate the effectiveness of the proposed D-HLDO method.

1. Introduction

Image feature extraction has attracted much attention from the science and industrial communities over the past decades owning to its wide applications in image retrieval, image registration, image analysis, object classification and biometrics. For a biometrics system, good image representation features are expected to have high discriminative ability so that the described image of one person can be easily distinguished from images of other ones. In addition, the features are supposed to be robust to noise, blurring and illumination changes. Therefore, the main concern of researchers is to improve the discrimination while maintaining the robustness in the design of image feature extraction method. In the past decade, there is a large amount of literature on developing image feature extraction methods.

In the previous works, such as SIFT [14], HOG [19] and WLD [29], we observe that the gradient orientation of each pixel plays an important role in image feature extraction. However, the gradient orientation, which is estimated by the local gradients directly, is not very reliable, because the local gradients are sensitive to noise and brightness changes. To tackle this problem and further enhance the discriminative power of image features, we presented a simple yet effective method called discriminative histogram of local dominant orientation (D-HLDO) for biometric image feature extraction. D-HLDO first captures the robust local dominant orientation via the PCA-based method. The local dominant orientation and the corresponding relative energy reveal sufficient local structural information of edges, textures, spots and so on. Then, the dominant orientation map and the relative energy map are divided into several overlapping regions. For each region, 1-D histogram is obtained by accumulating the relative energies of different dominant orientations. The combined histograms form an augmented image feature vector which contains all structural and spatial information of the image. Finally, the local mean based nearest neighbor discriminant analysis (LM-NNDA) [35] is used to get the low-dimensional and discriminative HLDO feature vector. The steps of our image feature extraction method are illustrated in Fig. 1. To show the effectiveness of the proposed D-HLDO method, we use five image databases which involve different recognition tasks: the AR, CMU PIE and FRGCv2.0 for face recognition, the PolyU Finger-Knucle-Print database for FKP recognition, and the PolyU Palmprint database for palm recognition.

The remainder of this paper is organized as follows. Section 2 briefly introduces the recent studies of image feature extraction; Section 3 develops our image feature extraction method D-HLDO and compares it with state-of-the-art algorithms. Section 4 describes the experimental methodology and results. Section 5 offers our conclusions and future work.

2. Backgrounds

This section mainly discusses the related literature of image feature extraction methods. Generally speaking, most of these

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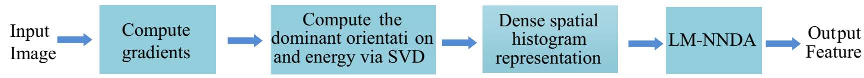

Fig. 1. An overview of our image feature extraction method.

methods can be roughly classified into two categories: subspace-based global feature and local descriptor feature.

The subspace-based global features focus on the content of the whole image. The main idea of these methods is seeking the optimal projection matrix with respect to the predefined criterion to project the original image into a low-dimensional subspace. Principal component analysis (PCA) and liner discriminant analysis (LDA) are two traditional subspace methods for feature extraction [1]. They have been widely used in pattern recognition and computer vision areas. Recently, many manifold learning algorithms for discovering intrinsic low-dimensional embedding of data were developed. The representative manifold learning methods are isometric feature mapping (ISOMAP) [2], local liner embedding (LLE) [3], Laplacian eigenmap [4], locality preserving projections (LPP) [5] and unsupervised discriminant projection (UDP) [6]. Many experiments show that these methods can find perceptually meaningful embeddings for face images. In addition, numerous feature extraction methods were put forward to deal with the real-world biometric problems [7–10]. Xu et al. [11] suggested a feature fusion method named matrix-based complex PCA for bimodal biometrics. Yang et al. [12] proposed a multi-manifold discriminant analysis (MMDA) method for image feature extraction. Gao et al. [13] presented an enhanced fisher discriminant criterion (EFDC) to extract robust and efficient features.

Compared with the global features, local descriptor features focus on describing the meaningful and the interesting characteristics in local regions. Scale invariant feature transform (SIFT) [14], as one of the most famous and popular image descriptors, performs well in the scenario of image matching and scene recognition. The SIFT descriptor is actually a 3-D histogram of gradient locations and orientations. The contribution of the location and orientation bins is determined by the gradient magnitude. In a comparative study [15], extensive experiments demonstrate the advantages of the SIFT and its invariant, GLOH (gradient location and orientation histogram), compared with other local image descriptors such as shape context, steerable filters, spin images, differential invariants and moment invariants. To further improve the SIFT descriptor, Ke and Sukthankar [16] applied PCA to the normalized gradient patch and developed the PCA-SIFT descriptor which is more compact and discriminative than SIFT. Bay et al. [17] presented an effective implementation of SIFT by relying on integral images for image convolutions. Bosch [18] introduced the dense SIFT (DSIFT) in conjunction with hybrid generative/discriminative approach for scene classification. Dalal and Triggs [19] proposed a histogram of orientation gradients (HOG) image descriptor which uses the normalized local gradient orientation in a dense overlapping grid to improve the performance of pedestrian detection. In addition, there are several attempts to improve the gradient orientation based image descriptors [20–23].

Local binary pattern (LBP) is an operator for image description based on the differences between central pixel and its neighbors over the local patch. LBP has received a great deal of attention in texture analysis, face recognition and video back-ground subtraction due to its simple and invariant to monotonic grayscale changes of the image [24,25]. Many LBP variants have been proposed and successfully applied to many areas. Tan and Triggs [26] gave a generalization of local texture descriptor named local tensor pattern (LTP) for face recognition, which is more discriminative and less sensitive to noise in uniform regions. Zhao and Pietikäinen [27] presented a method called LBP-TOP for dynamic texture and facial analysis. Moreover, a family of novel face image descriptors (e.g. three-patch LBP (TPLBP) and four-patch LBP (FPLBP)) has been developed, and they can capture statistics of local patch similarities [28]. Weber local descriptor (WLD) is a robust local image descriptor for texture analysis and human face detection [29]. Inspired by the physiological law, WLD simulates a human sensing his/her surroundings to describe the image features. WLD is actually a 2-D histogram contains differential excitation and orientation. Ngoc-Son et al. [48] applied the LBP-based structure on oriented edge magnitudes to construct a novel image descriptor, patterns of oriented edge magnitudes (POEM), for face recognition. Apart from the methods mentioned above, there are other LBP variants and applications; see [30–34].

3. D-HLDO: a novel image feature extraction method

As discussed in Section 1, the previous methods, such as SIFT, HOG and WLD, do not guarantee to obtain the reliable gradient orientation representation for classification purposes. To address this, we introduce the PCA-based method to compute gradient orientation in a local patch. This allows us to obtain the robust local dominant orientation for feature representation. LM-NNDA is further used to get the low-dimensional and discriminative features.

3.1. Principal component analysis for local orientation estimation

In this section, we mainly introduce the principal component analysis (PCA) based method to estimate the local gradient orientation. PCA is also referred to as the Karhunen–Loeve transform (KLT) [41]. It provides a set of optimal basis vectors to represent the given data and results in the minimum mean-square approximation error. PCA can be done by eigenvalue decomposition of the data covariance matrix or singular value decomposition (SVD) of the data matrix. Here, we introduce the method in terms of SVD.

Specifically, the gradient matrix over a $P \times P$ window (w_i) around the interesting point $f(x,y)$ of an image is defined as

$$\boldsymbol{G} = \begin{bmatrix} \vdots & \vdots \\ g_x(k) & g_y(k) \\ \vdots & \vdots \end{bmatrix}, \quad k \in w_i \tag{1}$$

where $g_x(k)$ and $g_y(k)$ denote the gradients of the image at point (x_k, y_k) in x and y directions, respectively. The covariance matrix of gradient vectors of points in the window w_i is defined as

$$\boldsymbol{C} = \boldsymbol{G}^T\boldsymbol{G} = \begin{bmatrix} \sum\limits_{k \in w_i} g_x(k)g_x(k) & \sum\limits_{k \in w_i} g_x(k)g_y(k) \\ \sum\limits_{k \in w_i} g_y(k)g_x(k) & \sum\limits_{k \in w_i} g_y(k)g_y(k) \end{bmatrix} \tag{2}$$

Actually, we can derive the meaningful local information of the patch w_i directly from the gradient matrix $\boldsymbol{G}$. The local dominant orientation is achieved by performing SVD of $\boldsymbol{G}$:

$$\boldsymbol{G} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^T \tag{3}$$

where $\boldsymbol{U}$ is a $P \times 2$ matrix, and $\boldsymbol{V}$ is a 2×2 matrix. For each matrix, the column vectors are orthogonal. $\boldsymbol{S}$ is a diagonal 2×2 singular value matrix representing the energy in the dominant orientation and its perpendicular direction; the first column vector of matrix