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Face recognition using locality sensitive histograms of oriented gradients

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ABSTRACT

In this paper, we propose a novel locality sensitive histograms of oriented gradients (LSHOG) for face recognition. The traditional histograms of oriented gradients (HOG) divide an image into many cells, and computed a histogram of gradient orientations over each cell. Unlike traditional HOG our proposed LSHOG compute a histogram of gradient orientations over the whole image at each pixel location. For each occurrence of a gradient direction value we add a locality sensitive parameter which can make the gradient direction value declines exponentially in regard to the distance between the pixel location of the gradient direction value and the pixel location where we are computing the histogram. Our proposed LSHOG take spatial information of face images into account which make it insensitive to noise such as occlusion and non-uniform illumination. LSHOG was applied to face recognition task. First, we use LSHOG to extract feature vectors of face images. Then, to show how different dimension reduction algorithms affect recognition accuracy, we choose several typical dimension reduction algorithms to reduce the dimensions of feature vectors of face images. We evaluated LSHOG and our proposed face recognition method on four benchmark face databases. Experimental results verify the feasibility and effectiveness of LSHOG and our face recognition method.

1. Introduction

Face recognition has been a hot topic for many years due to its many applications. Many researchers have proposed a variety of solutions of this task. We can broadly classified face recognition methods into subspace learning based method [1–10] and feature extraction based method [11–16]. Researchers of subspace learning based method believe that information of human faces, which can be utilized for face recognition, is a low-dimensional subspace embedded in a high-dimensional subspace space [6]. The aim of subspace learning algorithm is to find a map which can map samples in high-dimensional space into a low-dimensional one. The major drawback of subspace learning based method is that it equivalent dimensionality reduction to feature extraction, which neglect inherent features of human faces.

Feature extraction based method try to extract distinguished features of human faces for classification. Feature extraction is core steps of feature extraction based face recognition, and in this paper we will focus on the problem of feature extraction. There are many feature extraction method. In [11,12], local binary pattern (LBP) feature histograms are extracted from each small regions of face images. In [15], face images are represented by labeled graphs which are based on a Gabor wavelet transform. Dalal and Triggs proposed histograms of oriented gradients [17,18] for human detection. Dalal and Triggs divided an image into many cells, and computed a histogram of gradient orientations over each cell. Then, several connected cells combined into a block, and histograms of cells can be normalize in the block. The combination of all the histograms is the HOG feature vector of the image. Albiol et al. [14] firstly applied HOG descriptors to face recognition task, they extract HOG features of 25 landmarks localized by elastic bunch graph matching framework [15]. The authors in [16] adopts the similar HOG feature extraction method with the method proposed by Dalal and Triggs. Then principal component analysis (PCA) [1] or linear discriminant analysis (LDA) [2] were used to reduce the dimensions of HOG feature vectors.

The face recognition method proposed in [16] is belong to subspace learning based method and feature extraction based method at the same time, because it has the feature extraction process and the subspace learning dimensionality reduction process.

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Experimental results in [16] have shown that the performance of HOG descriptor plus dimensionality reduction algorithm is much better than using dimensionality reduction algorithm only.

A face image is a 2D matrix, but Dalal and Triggs's HOG feature extraction method does not take spatial information into account. Many face recognition methods fail to handle errors due to the presence of occlusion and non-uniform illumination on face images. To overcome the two limitations to some extent, in this paper, we propose a novel locality sensitive histograms of oriented gradients (LSHOG) for face recognition. LSHOG compute a histogram of gradient orientations at each pixel location, and each histogram takes the contributions of gradient orientations of every image pixel into account. For each occurrence of a gradient direction value we add a locality sensitive parameter which can make the gradient direction value declines exponentially in regard to the distance between the pixel location of the gradient direction value and the pixel location where we are computing the histogram. The main contributions of this paper are:

1. We first present LSHOG which take spatial information of face images into account which make it insensitive to noise such as occlusion and non-uniform illumination.
2. To reduce the computational cost and preserve discriminative information of LSHOG feature vector, we applied subspace learning algorithms to reduce the dimensions of LSHOG feature vectors before face classification. In order to show how different dimension reduction algorithms affect recognition accuracy, we choose several typical dimension reduction algorithms reduce the dimensions of feature vectors of face images.

The rest of this paper is organized as follows. In Section 2 we give a review of HOG. In Section 3 we first present the locality sensitive histograms of oriented gradients (LSHOG). This is followed by the report of experiments in Section 4, which evaluates LSHOG and our proposed face recognition method. In Section 5 we concludes the paper.

2. Face recognition using HOG

The extraction of a HOG feature vector of an image is done according to the following steps proposed by Dalal and Triggs [17,18].

1. Using gradient filter [− 1, 0, 1] with no smoothing [17] to compute the horizontal $G_x(x, y)$ and vertical $G_y(x, y)$ gradient of an image.
2. Compute the magnitude $|G(x, y)|$ and angle $\theta(x, y)$ of the gradient.

$$|G(x, y)| = \sqrt{G_x(x, y)^2 + G_y(x, y)^2} \tag{1}$$

$$\theta(x, y) = \arctan\left(\frac{G_y(x, y)}{G_x(x, y)}\right) \tag{2}$$

3. Divide an image into cells, and each cell has 8×8 pixels. Then, a histogram with nine orientation bins in 0°–180° [17] will be computed. Magnitude ($|G(x, y)|$) whose angle ($\theta(x, y)$) belongs to the same bin will be added up as the value of this bin.
4. Four connected cells combined into a block, and histograms of cells can be normalize in the block by $L2-Hys$ (Lowe-style clipped $L2$ norm) [17] normalization method. The combination of all the histograms is the HOG feature vector of the image.

After extracting HOG vectors of face images, the authors in [16] use PCA or LDA to reduce the dimensions of HOG feature vectors, which will make the classifier more efficient.

3. Locality sensitive histograms of oriented gradients

In this section we first present a novel locality sensitive histograms of oriented gradients (LSHOG) for face recognition and we will introduce the extraction process of a LSHOG feature vector of a face image in detail. There are four steps to extract a LSHOG feature vector from a face image, and step one and step two are the same as the process of HOG feature extraction.

Step 1. Using gradient filter [− 1, 0, 1] with no smoothing [17] to compute the horizontal $G_x(x, y)$ and vertical $G_y(x, y)$ gradient of an image.

Step 2. Compute the magnitude $|G(x, y)|$ and angle $\theta(x, y)$ of the gradient.

Step 3. Different from HOG, LSHOG do not divide an image into cells. LSHOG compute a histogram of nine gradient orientation bins in 0°–180° over the whole image at each pixel location. Let H_p^G denotes a LSHOG compute at pixel p, H_p^G is a nine dimensional vector. Our proposed LSHOG is defined as Eq. (3).

$$H_p^G(b) = \sum_{q=1}^{m\times n} \alpha \cdot V_b(\theta_q, b), \quad b = 1\ldots 9 \tag{3}$$

where the image size is $m \times n$, so $m \times n$ is the number of pixels of the image, θ_q is the gradient angle of pixel q, and $V_b(\theta_q, b)$ is defined as Eq. (3).

$$V_b(\theta_q, b) = \begin{cases} |G_q|, & if \quad \theta_q \in bin \quad b \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $|G_q|$ is the gradient magnitude of pixel q.

In Eq. (3), α is the locality sensitive parameter. We can use α to make pixels far away from the current pixel p have less weight. As we known, the closer the distance between two pixels, the higher the similarity of them. Hence, the contribution of pixels far away from target pixel p to H_p^G should be small.

The computational complexity of Eq. (3) will be very high. He et al. [19] have given an efficient calculation method for their proposed locality sensitive intensity histograms. The locality sensitive intensity histograms proposed by He et al. has an $O(NB)$ complexity, where N is the number of pixels and B is the number of bins [19]. The efficient calculation method given by He computed the locality sensitive intensity histograms by the gray value of each pixel, and the purpose of step three is computed the LSHOG by the gradient of each pixel. Hence, we can use the calculation algorithm proposed by He et al. to compute our LSHOG. Suppose there is a 1D image. Hence, the H_p^G of the image can be calculated by Eq. (5) [19].

$$H_p^G(b) = H_p^{G,\text{left}}(b) + H_p^{G,\text{right}}(b) - V_b(\theta_q, b) \tag{5}$$

where

$$H_p^{G,\text{left}}(b) = V_b(\theta_q, b) + \alpha \cdot H_{p-1}^{G,\text{left}}(b) \tag{6}$$

$$H_p^{G,\text{right}}(b) = V_b(\theta_q, b) + \alpha \cdot H_{p-1}^{G,\text{right}}(b) \tag{7}$$

let n_p^G denote the normalization factor at pixel p, n_p^G can be computed in the following way [19]:

$$n_p^G = n_p^{G,\text{left}} + n_p^{G,\text{right}} - 1 \tag{8}$$

where

$$n_p^{G,\text{left}} = 1 + \alpha \cdot H_{p-1}^{G,\text{left}} \tag{9}$$

$$n_p^{G,\text{right}} = 1 + \alpha \cdot H_{p-1}^{G,\text{right}} \tag{10}$$

We let $\alpha = e^{(-\frac{1}{\varepsilon \cdot W})}$, where W is the width of the 1D image, $\varepsilon \in (0, 1)$. The α is a locality sensitive parameter controlling the decreasing weight as a pixel moves away from the current pixel P. For 2D image,