

HOG-NPE: A Novel Local Description Operator for Face Image Recognition

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Abstract

The method of extracting robust feature sets from an image is a crucial issue for the areas of computer vision and pattern recognition. The nature of real data is a very high dimensional data. However, the hidden structure can be well characterized by a small number of features in most cases. As a result, the method of extracting a small number of good features is an important question in computer vision and pattern recognition, etc. We employ the Histograms of Oriented Gradient (HOG) to extract the robust feature sets of facial images, which is a local description operator that possesses a certain degree of invariance against geometric and photometric deformations. Neighborhood Preserving Embedding (NPE) which is a subspace learning algorithm is adopted to extract a small number of good features on the local description operators. We use the novel local description operator - HOG-NPE for facial image recognition, and several experiments on well-known facial databases are conducted, which demonstrate good performance and effectiveness of this novel local description operator.

Keywords: Good Features; Histograms of Oriented Gradient; Subspace Learning; Neighborhood Preserving Embedding

1 Introduction

The method of extracting robust feature sets has been an issue of concern in the field of machine learning, computer vision, pattern recognition, etc. Facial image recognition is also a challenging task when encountering practical problems such as illumination, occlusion, expression and deformation, etc. The method, *Histograms of Oriented Gradient* (HOG), is a kind of local description operator, which mainly possesses two advantages. Firstly, the local shape and appearances are well presented by capturing the edge or its gradient structure. Secondly, it possesses a good invariance against image geometry and optical deformation [1].

The nature of real data is a very high dimensional data. Practical algorithms do not perform well, and possess too many features which are not necessary or are redundant. Therefore, the

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method of extracting a small number of good features plays an important role in the fields of machine learning, computer vision, pattern recognition, etc. The underlying structure is well characterized by a small number of features in many cases [2-5]. As a result, the linear subspace learning will be appropriate for the exploration or capturing the intrinsic structure and, at the same time, obtaining the small computational cost [6-8]. One of the most popular linear subspace learning techniques is the *Principal Component Analysis* (PCA). PCA aims at preserving the global Euclidean structure on data manifold and only performs well when the manifold is embedded linearly in ambient space. While *Neighborhood Preserving Embedding* (NPE) aims at preservation of the local neighborhood (manifold) structure, which is less sensitive to outliers than PCA. In this paper, the HOG features were extracted and then a linear subspace with NPE was learned. And finally, we are able to gain a novel local description operator HOG-NPE [2].

The rest of this paper is organized as follows. In Section 2, the local description operator Histograms of Oriented Gradient (HOG) will be introduced. *Neighborhood Preserving Embedding* (NPE) is reviewed in Section 3. In Section 4, our novel local description operator HOG-NPE will be proposed, then, the experiment setup will be presented in Section 5 followed by the conclusion in Section 6.

2 Local Description Operator Histograms of Oriented Gradient (HOG)

Histograms of Oriented Gradient (HOG) algorithm is a local description operator, which is operated on small unit grids ('cells'). In actual operation, the image is divided into small regions of space, where a local one-dimensional histogram of gradient directions over pixels of the cell is accumulated. An example is demonstrated in the third image 'Cells of face' in Fig. 1. Before forming the one-dimensional histogram of gradient directions, it is necessary to implement an effective local contrast normalization over 'block' which includes, 2×2 cells, as shown in the last image in Fig. 1. Finally, the final description is constituted by the combined histogram entries. The method which involves normalizing the local histograms of gradient directions in a dense grid has two advantages: the first one is that the local appearance and shape of an object can be well characterized by the capturing gradient directions structure. The second advantage is that, it possesses a good invariance against image geometry and optical deformations. The steps are as follows [1, 9, 10].

(1) Compute the gradient. We employ a template $[-1 \ 0 \ 1]$ and $[-1 \ 0 \ 1]^T$ to convolve with the original image for each pixel, respectively in the x-axis and y-axis directions.

(2) Form the one-dimensional histogram of gradient directions over the pixels of the cell. The image is divided into small spatial regions called "cells". The size, for example, 8×8 pixels, with the number of bins of orientations 9, and the gradient direction is 180° or 360° . One-dimensional histogram of gradient directions over the pixels of each cell will be formed by collecting the statistical gradient information.

(3) Put cells into blocks. Along with the local variations in illumination and face image contrast, gradient strength also varies over a wide range. As a result, it is necessary to implement an effective local contrast normalization. In order to achieve better results, a Gaussian spatial window is applied for each block.