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Continuous rotation invariant features for gradient-based texture classification ☆

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ABSTRACT

Extracting rotation invariant features is a valuable technique for the effective classification of rotation invariant texture. The Histograms of Oriented Gradients (HOG) algorithm has been proved to be theoretically simple, and has been applied in many areas. Also, the co-occurrence HOG (CoHOG) algorithm provides a unified description including both statistical and differential properties of a texture patch. However, HOG and CoHOG have some shortcomings: they discard some important texture information and are not invariant to rotation. In this paper, based on the original HOG and CoHOG algorithms, four novel feature extraction methods are proposed. The first method uses Gaussian derivative filters named GDF-HOG. The second and the third methods use eigenvalues of the Hessian matrix named Eig(Hess)-HOG and Eig(Hess)-CoHOG, respectively. The fourth method exploits the Gaussian and means curvatures to calculate curvatures of the image surface named GM-CoHOG. We have empirically shown that the proposed novel extended HOG and CoHOG methods provide useful information for rotation invariance. The classification results are compared with original HOG and CoHOG algorithms methods on the CUReT, KTH-TIPS, KTH-TIPS2-a and UIUC datasets show that proposed four methods achieve best classification result on all datasets. In addition, we make a comparison with several well-known descriptors. The experiments of rotation invariant analysis are carried out on the Brodatz dataset, and promising results are obtained from those experiments.

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1. Introduction

Texture is an important characteristic of the appearance of objects and is a powerful visual cue, used in describing and recognizing object surfaces [1]. Texture analysis plays an important role in image processing, pattern recognition, and computer vision [2–8]. Texture classification methods usually consist of two steps of feature extraction and classification. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. To enhance the overall quality of texture classification, both the quality of the texture features and the quality of the classification algorithm must be improved [9–14].

There has been intensive research in developing robust features for texture classification with strong invariance to rotation, scale, translation, illumination changes [15–23]. Rotation invariant feature extraction is a difficult problem, thus many algorithms were proposed to achieve the rotation invariance [24,25].

The pioneer works to achieve rotation-invariant texture classification include generalized co-occurrence matrices (GCM) [26], polarograms [27], texture anisotropy [28], the methods based on Markov random field (MRF) [29] and autoregressive model. The wavelet based algorithms achieved effective classification performance [30–37]. Recently, the statistical based approaches have attracted considerable attention [38–40]. However, many of these approaches achieve the rotation invariance by shifting the discrete orientations. For example, the method of local binary pattern (LBP) [18] is proposed to achieve rotation invariance [41].

The gradient based features such as edges or orientation angles are widely used as feature descriptors in image processing. In order to identify objects in images effectively, gradient based edge features have been developed, which are edge orientation histogram [42], Histograms of Oriented Gradients (HOG) [43,44], co-occurrence HOG (CoHOG) [45], multilevel edge energy features [46], shapelets [47], and edge density [48]. The HOG method distributes the gradients into several orientation bins. HOG encapsulates changes in the magnitude and orientation of contrast over a grid of small image patches. HOG features have shown satisfactory performance in their ability to recognize a range of different object

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types including natural objects as well as artificial objects. CoHOG (Co-Occurrence Histograms of Oriented Gradients), an extension of HOG to represent the spatial relationship between gradient orientations, has been proposed and its effectiveness for pedestrian detection, human detection and medical image analysis has been demonstrated in [49–51].

According to a review [52], the extraction of basic features in images is based on two mathematical concepts: differential geometry and scale-space theory. The differential geometry approach uses the assumption that features can be obtained from the image based on local anisotropic variations of pixel intensities. This concept is strong and effective. Recently, the differential feature extraction approaches have attracted more attentions [53,54]. Among the different feature extraction methods, gradient-based methods were widely used in the past. These methods are effective in defining and describing significant image features. Hessian matrix information is a robust differential method and it has been widely used in many publications to extract the image features [55,56]. Compared with the conventional gradient, the Hessian matrix and its Eigen analysis are more reliable and robust in revealing the fundamental directions in data. In this study, we propose four novel methods to improve the classification performance of the HOG and CoHOG algorithms. The proposed four methods are based on Gaussian derivatives filters and Hessian matrix. Instead of using the conventional gradient operator in HOG and CoHOG algorithms, the second-order partial derivatives in Gaussian derivatives filters and Hessian matrix are more proper and stable to calculate the intensity and texture variations of image surface.

The rest of this paper is organized as follows. In Section 2, we will give a review of the original HOG and CoHOG algorithms. Section 3 presents the proposed new HOG and CoHOG algorithms based on Gaussian derivatives filters, Hessian matrix and Gaussian–mean curvatures. In Section 4, we test the performance of novel feature extraction algorithms on four standard texture datasets and discuss the effect of the normalization step on the classification performance. In Section 5, a series of rotation analysis experiments are performed. Furthermore, the characteristics of proposed descriptors are discussed in detail. The comparison results with the state-of-the-art the texture classification methods performed on Brodatz and UIUC datasets are shown in Section 6. The conclusions are given in Section 7.

2. Related works

2.1. Histograms of Oriented Gradients (HOG)

This section gives an overview of the HOG feature extraction process. The basic concepts of the HOG are the local object appearance and shape, which can be characterized by the distribution of the local intensity gradients or edge directions [57,58]. The gradients orientations are strong against lighting changes since the forming histogram provides rotational invariance.

For each key point, a local HOG descriptor from a block is computed. The block size is not restricted to construct an extensive set of texture features, which allow extracting high-discriminated features in order to improve classification accuracy and reduce computational time of classification algorithms [59,60]. HOG is a window based algorithm computed local to a detected interest point. The window is centered upon the point of interest and divided into a regular square grid ($n \times n$) [43,44]. This method consists of several steps.

First, the grayscale image was filtered to obtain x and y derivatives of pixels. The filter kernels were used to compute discrete derivative in the x and y direction. The gradient values at every image pixel were computed as follows:

$$\begin{aligned} f_x(x,y) &= I(x+1,y) - I(x-1,y) \\ f_x(x,y) &= I(x,y+1) - I(x,y-1) \end{aligned} \tag{1}$$

where f_x and f_y denotes x and y components of image gradient respectively. $I(x,y)$ denotes the pixel intensity at position (x,y). The magnitude and orientation is computed in Eqs. (2) and (3):

$$m(x,y) = \sqrt{f_x(x,y)^2 + f_y(x,y)^2} \tag{2}$$

$$\theta(x,y) = \tan^{-1}\left(\frac{f_y(x,y)}{f_x(x,y)}\right) \tag{3}$$

Second, the image intensity gradients are divided into layers based on their orientation. The original HOG descriptor uses unsigned gradients in conjunction with 9 bins (a bin corresponds to 20°) to construct the histograms of oriented gradients. Therefore, there are 9 layers of orientated gradient.

Finally, orientation histogram of every cell and larger spatial blocks $n \times m$ are normalized. To normalize the cells' orientation histograms, they should be grouped into blocks. Since a cell has k orientations, the feature dimension of each block is $n \times m \times k$ for each block. v denotes feature vector in a block $h_{(i,j)}$ denotes unnormalized histogram of the cell in the position (i,j) in a block. Although there are three different methods for block normalization, L1-Norm normalization is implemented as:

$$h'_{(i,j)} = \frac{h'_{(i,j)}}{\sqrt{\|v\|_1 + \varepsilon}} (\varepsilon = 1) \tag{4}$$

where ε is the small constant [43]. Here, ε is set to 1 empirically.

2.2. Co-Occurrence Histograms of Oriented Gradients (CoHOG)

The CoHOG feature descriptor is based on a co-occurrence matrix which is obtained from a 2D histogram of pairs of gradient orientations [45]. It performs on grayscale images. The co-occurence matrix expresses the distribution of gradient orientations at given offset over an image as shown in Fig. 1.

The combinations of neighbor gradient orientations provide reliable features of objects in images and this is very advantageous for object classification problems. The co-occurrence matrix C is obtained from $n \times m$ image of gradient orientations, and formulated in Eq. (5);

$$C_{i,j} = \sum_{p=0}^{n-1}\sum_{q=0}^{m-1} \begin{cases} 1 & \textit{if } I(p,q) = i \textit{ and } I(p+x, q+y) = j \\ 0 & \textit{otherwise} \end{cases} \tag{5}$$

where I indicates a gradient orientation image, i and j indicates gradient orientations and x, y denotes vertical and horizontal offsets. The gradient orientations from I are calculated in Eq. (6);

$$\theta = \tan^{-1}\left(\frac{v}{h}\right) \tag{6}$$

where v and h are the vertical and the horizontal components of gradient calculated by appropriate filters. Then, the orientations in the range $(0, 2\pi)$ are quantized into eight labels. Each label is used for representing an orientation. Thus, the size of the co-occurrence matrix C becomes 8×8. Six offsets are used in experiments. The co-occurrence matrix contains information on the local textures by using short-range offsets and the global textures by using long-range offsets [45,61].

The co-occurrence matrices are computed for each tiled regions with all offsets. Hence, the number of CoHOG descriptor features is $m \times n \times d^2$ where d is the number of gradient orientation bins, m is the number of tiled regions and n is the number of offsets. Finally, the CoHOG descriptor is determined as a vector by concatenating the components of all the co-occurrence matrices. The size of the original CoHOG descriptor is $2 \times 2 \times 6 \times 8^2 = 1536$.

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