Pedestrain Detection Based on a Gabor Weber Local Descriptor

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Abstract: Pedestrian detection has attracted more and more attention in recent years. In this paper, a novel pedestrian detection method based on Gabor Weber Local Descriptor (GWLD) was proposed. According to the pedestrian's characteristics, the sliding window technique was adopted. Firstly, Gabor transforms were performed on the sliding window, and then the Weber Local Descriptor (WLD) was extracted over the average Gabor feature maps. Finally, the GWLD histogram was constructed to character the sliding window. Experimental results on INRIA pedestrian dataset and Daimler Chrysler (DC) pedestrian dataset validate that the effectiveness of the proposed GWLD detector. Comparing with the other pedestrian detection methods, the proposed GWLD method performs better.

1. Introduction

Pedestrian detection has become significant interest in many practical applications[1,2], such as video surveillance, automotive systems and advanced robotics. However, detecting human in images/videos has been proven to be a challenging task because of the wide variability in appearance due to clothing, articulation and illumination conditions. Therefore, a more discriminative and robust descriptor is expected to improve the performance.

Currently, a number of detectors have been proposed for pedestrian detection. These methods offer different features to tackle this problem, such as Haar wavelets[3], scale invariant feature transform (SIFT) descriptors[4], edge templates[5], Gabor filters[6], covariance descriptor[7], Weber local descriptor (WLD)[8], adaptive contour features[9] and histograms of oriented gradients (HOG)[10]. Among these methods, the HOG method has shown great success. However, this method only uses the gradient orientations, the WLD method consisting of the differential excitation and the gradient orientation has acquired better performance for pedestrian detection[8]. However, the WLD method is very sensitive to noise. Unlike WLD, the methods based on Gabor wavelets is less sensitive to noise because the Gabor features are extracted in local regions covered by Gabor filters' support, and so they can smooth over noise.

Inspired by the success of WLD and Gabor wavelets for pedestrian detection, in this paper, we present a simple, yet very powerful and robust local descriptor that implements the concept of WLD within a Gabor wavelets framework. More specifically, we first utilize a Gabor wavelets filter bank to filter the input image at different scales and different orientations. Then several WLD histograms are computed based on the obtained filter responses. We call the descriptor as "Gabor Weber Local

Descriptor" (GWLD). Experimental results indicate that the histogram of GWLD can be used as a proper pedestrian detection descriptor.

2. Proposed Approach

In pedestrian detection, the robust feature representation strongly influences the detecting performance. In this section, the proposed method: Gabor and Weber Local Descriptor based pedestrian detection is presented. The objective of this work is to develop an effective and efficient method for pedestrian detection.

2.1. WLD Feature Extraction

In this section, we briefly review the WLD descriptor proposed by Chen et al. [11], which consists of two components, one is differential excitation (ξ) and the other is orientation (θ). Differential excitation $\xi(x_c)$ of a current pixel x_c is computed by the pixel and its neighbor pixels. According to [11], it is a function of the ratio between the relative intensity differences of the current pixel against its neighbours and the intensity of the current pixel. The relative intensity difference of the current pixel against its neighbours is calculated using a filter:

$$v_s^{00} = \sum_{i=0}^{p-1} (\Delta x_i) = \sum_{i=0}^{p-1} (x_i - x_c) \tag{1}$$

where x_i ($i = 0, 1, 2, \mathrm{L}, p-1$) represents the i-th neighbour of x_c and p is the number of the neighbour pixels. Therefore, the differential excitation of the current pixel $\xi(x_c)$ is computed as:

$$\xi(x_c) = \arctan\left[\frac{v_s^{00}}{x_c}\right] = \arctan\left[\sum_{i=0}^{p-1}\left(\frac{x_i - x_c}{x_c}\right)\right] \tag{2}$$

The orientation is the gradient orientation of the pixel, which is computed as:

$$\theta(x_c) = \arctan\left(\frac{v_s^{11}}{v_s^{10}}\right) \tag{3}$$

where v_s^{11} and v_s^{10} are respectively calculated as:

$$v_s^{11} = x_5 - x_1, \quad and \quad v_s^{10} = x_7 - x_3 \tag{4}$$

After obtaining the differential excitation $\xi(x_c)$ and gradient orientation $\theta(x_c)$ of each pixel x_c, the 2D histogram is obtained by:

$$WLD_{2D}(r,t) = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \delta(\xi(x_{i,j}),r)\delta(\theta(x_{i,j}),t) \tag{5}$$

With

$$\delta(x, y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \qquad (6)$$

where $M \times N$ represents the image size, $x_{i,j}$ is the pixel on location (i, j) in the image, $r = 0, 1, \text{L}, R-1$, $t = 0, 1, \text{L}, T-1$, R is the number of the differential excitation bins and T the dominant orientation.

2.2. Gabor Wavelets

A 2-D Gabor function g(z) is a 2-D Gaussian function modulated by a complex exponential in the spatial domain, which can be written as [12]:

$$g_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{(-\|k_{u,v}\|^2 \|z\|^2 / 2\sigma^2)} (e^{ik_{u,v}z} - e^{-\sigma^2/2}) \qquad (7)$$

where u and v represent the orientation and scale of the Gabor filters, respectively. $\|g\|$ denotes the 2-norm operator, σ is the standard deviation of the Gaussian function, $z = (x, y)$ is the pixel location in the image, $k_{u,v} = k_v e^{i\varphi_u}$, $k_v = k_{max} / f$, $\varphi_u = \pi u / 8$, k_{max} is the maximum frequency and f is the spatial factor between different filters in the frequency domain.

In this paper, five scales ($v = 0, 1\text{L}, 4$) and eight orientations ($u = 0, 1\text{L}, 7$) of Gabor filter banks are adopted, therefore, we can obtain 40 Gabor magnitude maps for each image, and the parameters are set as $\sigma = 2\pi$, $k_{max} = \pi / 2$, $f = \sqrt{2}$. Let $I(z)$ be a gray image, its filtering result with a Gabor filter is defined as:

$$M_{u,v}(z) = I(z) * g_{u,v}(z) \qquad (8)$$

where $*$ denotes the convolution operator.

2.3. Proposed GWLD Feature Representation

After Gabor filtering, 40 Gabor magnitude maps for each image are obtained that will induce the high-dimensional features. In order to reduce the dimensionality for real-time pedestrian detection, an average Gabor magnitude map is calculated based on the 40 Gabor magnitude maps. Then, the GWLD feature (ξ, θ) for each pixel is extracted from the average Gabor magnitude map. As mentioned in section 2.1, the 2D GWLD histogram can been constructed. Similar to[8], the $GWLD_{2D}$ is encoded into a 1D $GWLD_{1D}$ histogram for pedestrian detection.

As suggested in[8], we also let $R = 6$ for approximately simulating the variances of high, middle or low frequency in a given image. The regions of high variance in a given image are paid more attention compared with the flat regions. Thus, different weights are assigned to different differential excitation segments SH_r for a better performance, which have been validated their effectiveness for pedestrian detection[8].

2.4. Similarity Measurement

Many similarity measurement approaches have been presented for histogram matching. However, the Support Vector Machine (SVM) approach remains a popular choice for pedestrian detection because of its good performance and computational efficiency. In[8], based on the SVM classification, the competitive results were obtained. In this paper, the objective of this work is to validate the effectiveness of the proposed GWLD method for pedestrian detection. The linear SVM classifier is adopted in our experiments.

3. Experimental Results

To validate the effectiveness of the proposed GWLD method for pedestrian detection, the experiments are performed on two popular pedestrian datasets, INRIA dataset and Daimler Chrysler (DC) dataset. Inspired by the WLD feature for pedestrian detection[8], we also divide the image window into small cells, for each cell, a local $GWLD_{1D}$ histogram is computed. Then the $GWLD_{1D}$ histograms from different cells are then concatenated to describe the current scanning window.

3.1. Result Evaluation on INRIA Dataset

The INRIA pedestrian dataset introduced in [8] is significantly hard because of wide variety of articulated poses, variable appearance/clothing, illumination changes and complex backgrounds. Results on per-window classification accuracy are reported using the conventional Detection Error Tradeoff (DET) curve on a log-log scale, that is, miss rate ($\dfrac{FalseNeg}{FalseNeg + TruePos}$) versus FPPW.

Similar to [8], the cell size of 16×16 pixels is adopted. Our proposed GWLD detector is the combination of Gabor feature and WLD feature. Figure 1 shows that the GWLD method performs better than either the Gabor method or the WLD method. Also, an extensive experiment comparing with the HOG method, MWLD method, and HOG-LBP method is carried. Figure 2 shows the comparison results of the four methods. From this figure, it can be seen that our proposed GWLD method outperforms the other methods.
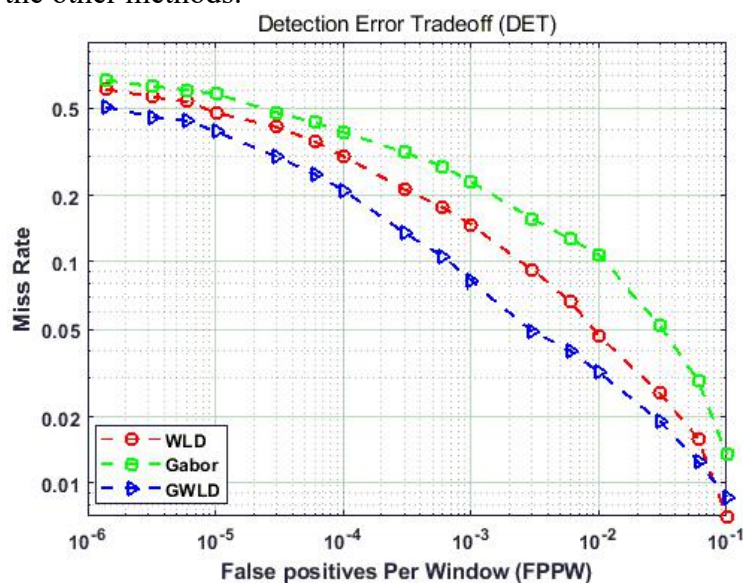

Figure 1: The comparison between the GWLD method and the WLD, Gabor method on INRIA dataset.

3.2. Result Evaluation on Daimler Chrysler (DC) Dataset

The second dataset we used for experiments is the Daimler Chrysler (DC) pedestrian Benchmark dataset [13]. In this work, the training and testing datasets are the same as the experimental set in [8]. Figure 3 shows that the GWLD method also performs better than the Gabor method and the WLD method. Also, Figure 4 shows the performance comparison between our proposed GWLD method and the MWLD method, HOG method and HOG-LBP method on DC dataset. From this figure, one could also conclude that our proposed GWLD method still outperforms the MWLD method, HOG method and HOG-LBP method.
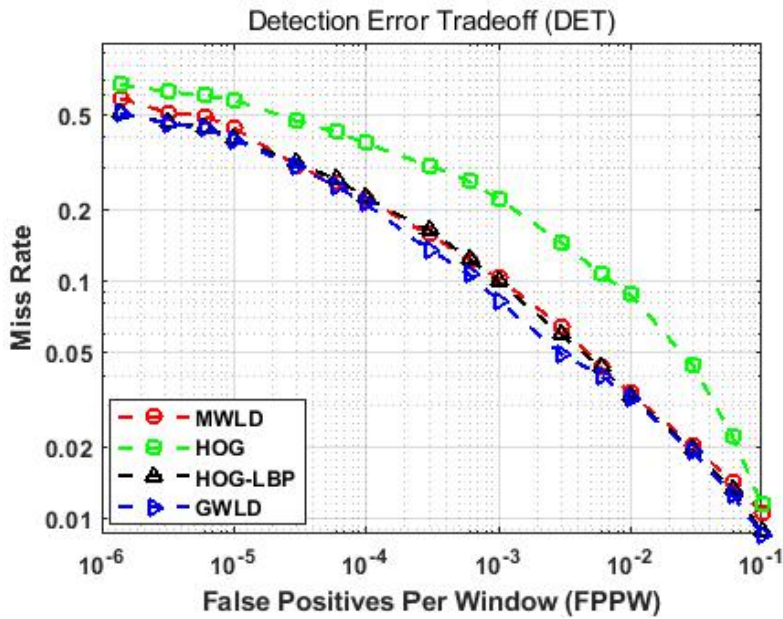

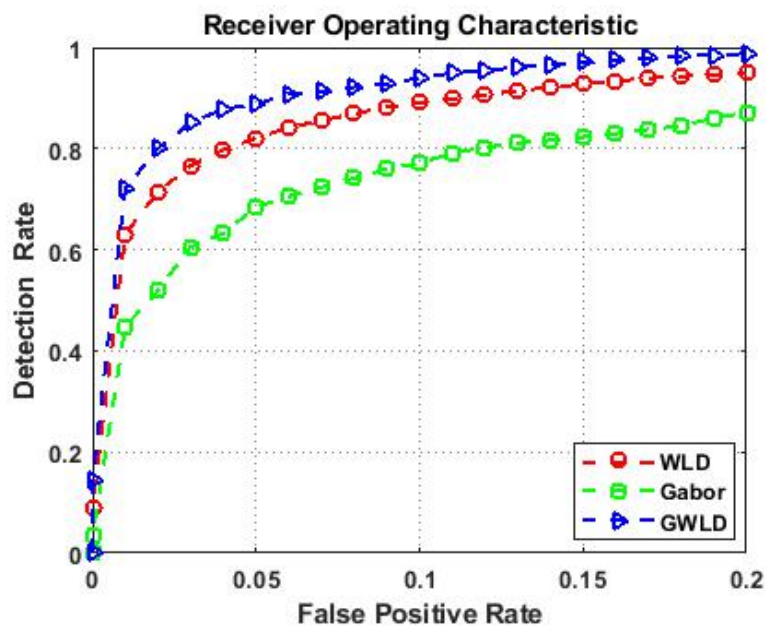Figure 2: The comparison between the GWLD method and the other methods on INRIA dataset.

Figure 3: The comparison between the GWLD method and the WLD, Gabor method on DC.

4. Conclusions

This paper has proposed an effective and efficient feature descriptor (GWLD) for pedestrian detection, which is constructed by computing the WLD histogram over the average Gabor magnitude maps of the input image. The sliding window technique was adopted and then the proposed GWLD detector to character the feature of the sliding window. Experimental results on INRIA pedestrian dataset and Daimler Chrysler (DC) pedestrian Benchmark dataset validate that the effectiveness of the proposed GWLD detector. Comparing with the MWLD method, HOG method and HOG-LBP method, the GWLD method performs better.
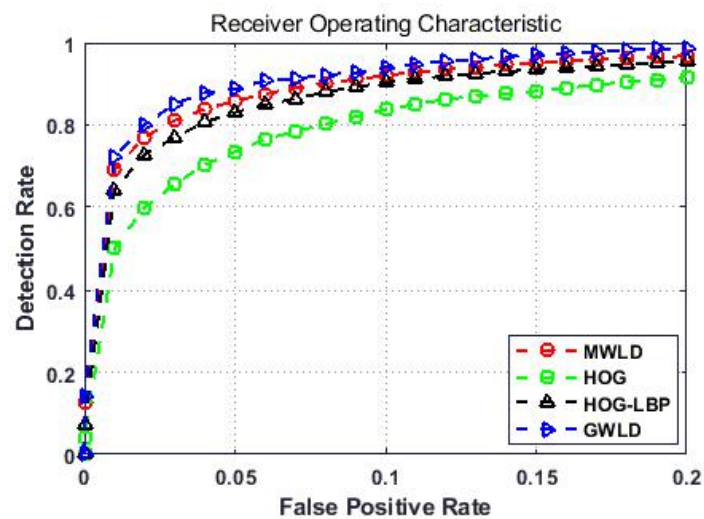
Figure 4: The comparison between the GWLD method and the other methods on DC.

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