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A Novel Human Detection Algorithm Based on Foreground Segmentation

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Abstract

In computer vision applications, human detection occupies an important position. HOG (Histograms of Oriented Gradient) is a classical algorithm which was used in the area of object detection. But the complex background would greatly affect the test accuracy when taking HOG as a human characteristic for human detection. In order to improve the accuracy of human detection, this paper applied a new algorithm which was based on foreground segmentation. We could get each closed region by Oriented Watershed Transform and Ultrametric Contour Map, then the foreground and the background could be distinguished. Finally we removed the background and calculated the foreground characteristic. The experimental results show that this approach was effective in improving detection accuracy.

Keywords: Human Detection; HOG; Foreground Segmentation; Closed Region

1 Introduction

In recent years, pedestrian detection and location are the topical issues in the field of computer vision and image processing, and is applied to many other fields. Pedestrian detection, location's accuracy and speed directly affect the follow-up work, so the detection and location technology have a great deal of attention. The detected images always have noise because of weather, light and in particular the effects of complex environmental background, which creates a lot of difficulties in Pedestrian detection and location.

At present, human detection is usually based on statistical classification methods [10-11]. Human detection is seen as a problem of classification of humans and non-humans, and its step is extracting the body characteristics and pattern recognition classification [1]. Existing feature

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extraction methods such as the wavelet feature, SIFT [2], Shape Context [3], PCA [4] and so on, makes some calculations on the dense, unified space unit, and in order to improve performance, there isneed to standardize the contrast of pixel in overlapping location. Dalai [5] and others proposed the HOG (Histograms of Oriented Gradient, HOG), which was used in target detection for pedestrians earlier. It is a better method in the field of pedestrian detection. It doesn't consider characteristics from the overall image. The gradient and edge direction histogram of each pixel are calculated on a gradient according to the images. We then obtained some gradient vectors. This method has a better robustness for changes in the morphology of the human body. Due to the interference of complex image background, the accuracy of detection and location will be influenced.

In this paper, we use the foreground segmentation method to reduce the impact of complex background on final detection results during pedestrian detection process.

2 HOG Feature Extraction and SVM Classification

When pedestrian is detected, the characteristics of the human body needs to be extracted, which is a prerequisite for classification and pedestrian detection. The basic steps of traditional HOG feature extraction are as follows.

2.1 Enter Image

Enter the image which will be processed, then we calculate the grayscale value of each pixel. Gradient calculation formula is as follows:

$$d_x(x, y) = f(x+1, y) - f(x-1, y) \tag{1}$$

$$d_y(x, y) = f(x, y+1) - f(x, y-1) \tag{2}$$

where $f(x, y)$ is the grayscale values of each pixel, $d_x(x, y)$ is derivative of the pixel (x, y) in the direction of x, $d_y(x, y)$ is derivative of the pixel (x, y) in the direction of y.

$$G(x, y) = \sqrt{d_x(x, y)^2 + d_y(x, y)^2} \tag{3}$$

$$\theta(x, y) = \tan^{-1}(d_y(x, y)/d_x(x, y)) \tag{4}$$

where $G(x, y)$ is Gradient amplitudes on the pixel (x, y), $\theta\ (x, y)$ is Gradient direction on the pixel (x, y).

2.2 Generating Eigenvectors

After we obtain the gradient amplitudes and gradient direction of each pixel, we build a block by 16×16 pixels. For each block, there are four 8×8 cells, and for each cell, there are nine bins. We divide 2π into 9 parts. Then we vote in the interval of $2\pi/9$ by the gradient direction of each pixel, and assume the gradient amplitudes as weight. So there are 36 dimension eigenvectors in a block.