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On-road precise vehicle detection system using ROI estimation

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***Abstract*— In this paper, we propose a new on-road vehicle detection system. Appearance of vehicles in image has various ratios because of its many kinds of models such as sedan, SUV and truck. For this reason, using ROI with fixed ratio can cause the degradation for detecting vehicles of various models. To solve this problem, we propose a new vehicle detection system using estimating ratio of vehicles. The proposed method estimates the ratio of vehicle ROI and extracted feature based evaluated ratio. It shows robust detection performance for various vehicle models because it extracts the feature from compact ROI with exact vehicle size. In our experiments, histogram of oriented histogram (HOG) feature and support vector machine (SVM) are used for the vehicle detection system. In order to evaluate the detection performance, the Pittsburgh dataset including various vehicle models such as sedan, SUV, truck and bus is used. In this dataset, it is shown that the proposed method is more robust than previous works to detect various vehicle models.**

I. Introduction

Vehicle detection is an important system to provide safety and comfort for drivers. From now on, applying machine vision technologies to vehicle detection has been researched in Intelligent Transportation System (ITS) [1], [2]. Most of them consist of features and classifiers. Focusing on features for vehicle detection, HOG [3], Haar-like wavelet [4] and Gabor feature [5] are generally used. Haar-like wavelet takes less computational time than HOG or Gabor feature. Instead, the detection performance using Haar-like wavelet is lower than HOG or Gabor feature. Focusing on classifiers for vehicle detection, the support vector machine (SVM), the Adaboost [6] and a Neural network (NN) are applied to train various features. Recently, Latent SVM has been researched for part-based deformable model [7]. This model can capture significant variation in object appearance.

Most of previous methods, however, do not consider vehicle ratio defined by vehicle height per width. Using fixed vehicle ratio causes inevitable false negatives and has difficulty to detect vehicle compactly because of various kinds of vehicles such as truck, bus, SUV and sedan. In this paper, we focus on estimating the vehicle ratio and generating efficient ROI in order to detect vehicles compactly.

II. Proposed Method

In this paper, the proposed vehicle detection system is based on sliding window approach. In sliding window

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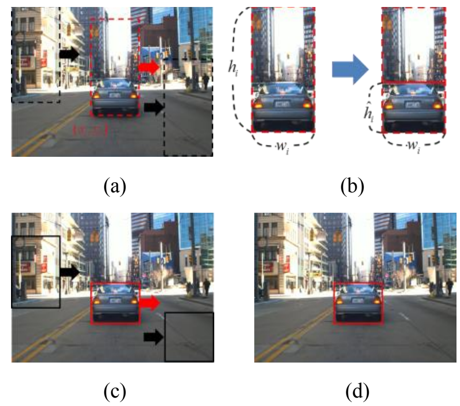

Figure 1. The framework of the proposed method. (a) shows the sliding window approach to estimate vehicle height. (b) is the result of estimating vehicle height. (c) shows efficient ROIs after estimating vehicle height. (d) the vehicle detection result using HOG and SVM in efficient ROIs.

approach, the ROIs are generated by searching whole image with multiple scales of window with fixed ratio. Fig. 1 shows the framework of the proposed method. The i -th window is defined by $\mathbf{w}_i = (x_i, y_i, w_i, h_i)$ where (x_i, y_i) is the left-lower position of the window, w_i , h_i are the width, height of the window, respectively. The estimated vehicle height is denoted by $\hat{h}_i$, so the efficient i -th ROI can be defined by $\hat{\mathbf{w}}_i = (x_i, y_i, w_i, \hat{h}_i)$. In this framework, estimating vehicle height is important part and main contribution of this paper. It consists of three parts: Measuring symmetric information, extracting horizontal edge and assigning weight.

A. Measuring Symmetric Information

Measuring symmetric information consists of three steps as follows.

1) First, the window is flipped horizontally to make a mirror image. Generally, the window area that is horizontally symmetric has high similarity value.

2) In order to evaluate similarity, HOG is used because HOG is more robust than features using intensity for various illuminations. HOG feature vector can be defined by

$$\mathbf{H} = \left[\mathbf{F}_{1,1}, \cdots, \mathbf{F}_{I,1}, \cdots, \mathbf{F}_{1,J}, \cdots, \mathbf{F}_{I,J} \right] \tag{1}$$

where $\mathbf{F}_{i,j} = \left[B_{i,j}^1, \cdots, B_{i,j}^T \right]$ denotes the histogram of (i,j) block and $B_{i,j}^t$ denotes sum of gradient magnitudes according to orientation bin t in (i,j) block and i , j , I , J are the row, column index, the number of row, column of HOG block respectively.

3) Using HOG of the window $\mathbf{H}_W$ and HOG of the flipped window $\mathbf{H}_F$, the similarity between two HOGs is defined by

$$\mathbf{S} = \sqrt{\mathbf{H}_W \circ \mathbf{H}_F} = \left[\mathbf{s}_{1,1}, \cdots, \mathbf{s}_{I,1}, \cdots, \mathbf{s}_{1,J}, \cdots, \mathbf{s}_{I,J}\right] \quad (2)$$

where $\circ$, $\mathbf{s}_{i,j}$ denote the componentwise multiplication, the similarity of (i, j) block, respectively. The symmetric information of j-th position is estimated by summing all the 1-norm of similarity in j th row as $m_j = \sum_{i=1}^{I} \left\| \mathbf{s}_{i,j} \right\|$. Finally, the accumulated symmetric information for estimating vehicle height is defined by $M_j = \sum_{t=0}^{J-j} \left(m_{J-t} - T_s \right)$ where T_s is threshold which makes low symmetric information to be negative. As a result, accumulated symmetric information is used as a key factor to estimate vehicle height.

B. Extracting Horizontal Edge

Not only symmetric information but also horizontal edge is an important factor to estimate vehicle height. The horizontal edge is also computed from HOG feature vector $\mathbf{H}_W$. The horizontal edge is defined by $E_j = \sum_{i=1}^{I} B_{i,j}^{t_0}$ where t_0 denotes the horizontal orientation bin.

C. Assigning Weight

Assigning weight into each j-th position is also an important procedure to estimate vehicle height exactly. Statistically, the distribution of vehicle ratios can be modeling by Gaussian function. In fact, it is difficult that vehicle ratio is lower than 0.5 or higher than 1.5. Therefore, assigning the weight is effective to reduce the false estimation_of vehicle ratio. In the proposed method, the weight is defined by

$$W_j = \mathcal{N}\left(j \,|\, \frac{J}{2}, \sigma \right) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{\left(j - J/2 \right)^2}{2\sigma^2} \right) \quad (3)$$

where $\mathcal{N}(\bullet)$ denotes the normal distribution. We suppose the mean of $\mathcal{N}(\bullet)$ as $\frac{J}{2}$ which means the vehicle ratio is 1 because most of vehicles has the ratio of 1.

D. Estimating vehicle height

By combining symmetric information M_j, horizontal edge E_j and weight W_j, the total score for estimating vehicle height is defined by

$$\mathbf{T} = \left[T_1, \cdots, T_J\right], \;\; T_j = M_j \cdot E_j \cdot W_j. \quad (4)$$

As a result, the vehicle height is estimated by selecting the position of which total score is maximum.

III. Experiment

In this section, a total of 11021 vehicles in Pittsburgh dataset are used to evaluate the performance of estimating vehicle height. To verify efficient ROIs, detection performance of HOG - SVM is used. Fig. 2 shows detection performances of previous method and proposed method. The previous method defined the vehicle ratio as 1. As shown in Fig. 2, the ROC curve shows that the proposed method has better detection performance than previous methods. When FPPI is over than 2.5, the previous method is better than proposed method. However, the FPPI of 2.5 means two or three false positives occur in every frame. Therefore, the detection performance degradation is negligible when FPPI is over 2.5.

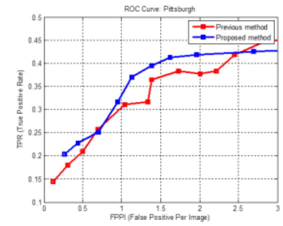

Figure 2. The detection performances of FPPI (False positive per image) vs TPR (True positive rate).

IV. Conclusion

In this paper, on road precise vehicle detection system is proposed. In the situation for requiring vehicle position and size exactly, the precise vehicle detection is very important. For the precise vehicle detection, we generate efficient ROIs using vehicle height estimation. In the experiment, we compare the proposed method with previous method and show the advantage of the proposed method.

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