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A rapid learning algorithm for vehicle classification

Xuezhi Wen [a,b], Ling Shao [c,*], Yu Xue [a,b], Wei Fang [a,b]

[a] Jiangsu Engineering Center of Network Monitoring, Nanjing University of Information Science and Technology, Nanjing 210044, China
[b] School of Computer and Software, Nanjing University of Information Science and Technology, Nanjing 210044, China
[c] Department of Computer Science and Digital Technologies, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK

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ABSTRACT

AdaBoost is a popular method for vehicle detection, but the training process is quite time-consuming. In this paper, a rapid learning algorithm is proposed to tackle this weakness of AdaBoost for vehicle classification. Firstly, an algorithm for computing the Haar-like feature pool on a 32×32 grayscale image patch by using all simple and rotated Haar-like prototypes is introduced to represent a vehicle's appearance. Then, a fast training approach for the weak classifier is presented by combining a sample's feature value with its class label. Finally, a rapid incremental learning algorithm of AdaBoost is designed to significantly improve the performance of AdaBoost. Experimental results demonstrate that the proposed approaches not only speed up the training and incremental learning processes of AdaBoost, but also yield better or competitive vehicle classification accuracies compared with several state-of-the-art methods, showing their potential for real-time applications.

1. Introduction

Vehicle detection is an important component in many related applications, such as self-guided vehicles, driver assistance systems, intelligent parking systems, or measurement of traffic parameters, including vehicle count, speed, and flow. A recent trend is to apply vision-based techniques to analyze vehicles. However, vision-based vehicle detection is a challenging topic due to the huge within-class variability. For example, vehicles may vary in shape, size, and color. Moreover, vehicle appearance depends on its pose and may be affected by nearby objects. Complex outdoor environments, e.g., illumination conditions, cluttered background, and unpredictable interactions between traffic participants, are difficult to be controlled. Moreover, on-board vehicle detection systems have high computational requirements. They need to be able to process acquired images in real-time to save more time for driver reaction. Although it is a challenging task to be accomplished, many optical sensor based vehicle detection algorithms and systems have been proposed and implemented. The majority of them follow two basic steps: (1) hypothesis generation (HG) and (2) hypothesis verification (HV) (see Fig. 1). The HG step is used for generating the locations of potential vehicles. Methods reported in the literature fall into one of the following three basic categories: knowledge-based, stereo-vision-based and motion-based. Visual saliency or attention approaches [6,9,10] can be applied as a preprocessing model for the HG step. The HV step is used for removing the false detections. HV approaches can be classified into two main categories: (1) template-based and (2) appearance-based.

For the above two steps, the HV step is a prerequisite for robust and accurate vehicle detection. Template-based methods need to use thousands of predefined patterns of the vehicle class and perform correlation between the test image and the template, which makes them time-consuming. In addition, template-based methods are sensitive to the varying background

* Corresponding author. Tel.: +44 1142225841.
E-mail address: ling.shao@ieee.org (L. Shao).

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(e.g. buildings, bridges and guardrails). Therefore, appearance-based methods are more common in the vision-based vehicle detection literature. Appearance-based methods, which rely on the machine learning, learn the characteristics of the vehicle class from a set of training images which capture the variability of the vehicle appearance. Usually, the variability of the non-vehicle class is also modeled to improve the performance. Firstly, each training image is represented by a set of local or global features. Then, the decision boundary between the vehicle and nonvehicle classes is learned by training a classifier. There are at least two fundamental challenges faced by appearance-based validation methods: the accuracy and the processing time.

In this paper, we focus on the investigation of the processing time of the machine learning methods, specifically, seeking solutions to speed up the training and incremental learning processes based on AdaBoost. We first design a Haar-like feature extraction method to represent a vehicle's edges and structures, and then propose a rapid feature selection algorithm by using AdaBoost due to the large pool of Haar-like features. Finally, we design an incremental learning algorithm to improve the classification performance significantly. Experimental results demonstrate that the proposed approaches not only speed up both the training process and the incremental learning process of AdaBoost, but also achieve competitive classification accuracies compared with several state-of-the-art methods.

The rest of the paper is organized as follows. In Section 2, we review the related work for vehicle detection by using appearance-based approaches. In Section 3, we present an algorithm for computing Haar-like features. A fast feature selection method for AdaBoost is reported in Section 4. Section 5 introduces the fast incremental learning algorithm based on AdaBoost. Experimental results and analysis are described in Section 6. Section 7 concludes this paper.

2. Related work

Machine learning methods are becoming increasingly popular for their high performance, robustness and easy operation, which have been applied to many fields (such as face recognition, pedestrian detection and vehicle detection) [26,30,35]. The machine learning methods used in HV is treated as a two-class pattern classification problem: vehicle versus non-vehicle. These methods usually consist of two processes: feature representation and classification. In the following part, we will present a detailed introduction of these two processes respectively.

2.1. Feature representation

Given the huge intra-class variabilities of the vehicle class, one feasible approach is to learn the decision boundary based on training a classifier using the feature sets extracted from a training set. Various feature extraction methods have been investigated in the context of vehicle detection. Based on the used methods, the features extracted can be classified as either global or local.

Global features are obtained by considering all the pixels in an image. Wu and Zhang [45] used standard Principal Component Analysis (PCA) for feature extraction. Although detection schemes based on global features, such as those described in [13,24,29,31,40,45], perform reasonably well, an inherent problem with global feature extraction approaches is that they are sensitive to local or global image variations (e.g., viewpoint changes, illumination changes, and partial occlusion).

Local features, on the other hand, are less sensitive to the effects faced by global features. Moreover, geometric information and constraints in the configuration of different local features can be utilized either explicitly or implicitly [33,48]. An overcomplete dictionary of Haar wavelet features was utilized in [27] for vehicle detection. Sun et al. [39] went one step further by arguing that actual values of wavelet coefficients are not very important for vehicle detection. They used quantized coefficients to improve detection performance. Using Gabor filters for vehicle feature extraction was investigated in [38]. Gabor filters provide a mechanism for obtaining orientation and scale related features. The hypothesized vehicle subimages were divided into nine overlapping subwindows, and then Gabor filters were applied on each subwindow separately. Furthermore, Sun et al. [37] combined Haar wavelet with Gabor features to represent a vehicle image patch. Scale invariant feature transform (SIFT) features [22] were used in [47] to detect the rear faces of vehicles. In [4], the histogram of oriented gradients (HOG) features were extracted in a given image patch for vehicle detection. In [18], a combination of speeded up robust features (SURF) [2] and edges was used to detect vehicles in the blind spot. The main drawback of the above local features is that they are quite slow to compute.

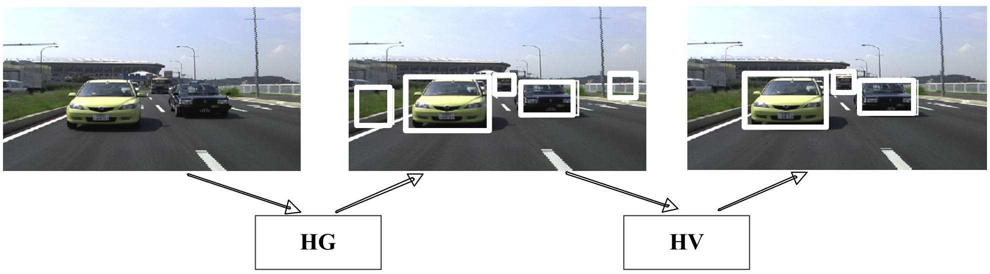

Fig. 1. Vehicle detection process.