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Improved vehicle detection system based on customized HOG

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***Abstract*— Recently, obstacles detection and identification task in ADAS is a well-established research field. Histogram of oriented gradients (HOG) is one of the most effective obstacle feature extraction approaches to the study. In this paper, an optimization detection system based on a customized HOG descriptor is presented and investigated to achieve an accurate vehicle recognition system.**

The key concept is to distribute an amplification factor for each bin weight according to its contribution in the vehicle-extracted features. Performance studies using a Linear SVM classifier in MATLAB and heterogeneous databases of vehicle and non-vehicle images prove the effectiveness of our approach.

***Keywords*— ADAS; HOG features; vehicle detection; MATLAB.**

I. Introduction

Automotive Driver Assistance System (ADAS) application is motivated, lucklessly, by the number of killed in road accidents each year. Object recognition in images supplied from the camera has become one of the most interesting technologies to reduce traffic accidents [1].

In this context, our application interested in detecting and recognizing different obstacles in an urban environment. In fact, it is aimed at helping drivers to see the road scene and dangerous driving situations in order to reduce traffic accidents with an automotive monocular camera. A typical computer vision systems chain for obstacle detection is presented in Fig 1. In this work, we will focus on vehicle’s detection and identification located ahead of driver. The process is included in the conventional passive supervised machine learning which comprises of a descriptor / classifier pair. According to the state of the art [2,3,4,5,6], the best result is achieved by combining a HOG descriptor and linear SVM classifier, that’s explain the choice of this couple in our work.

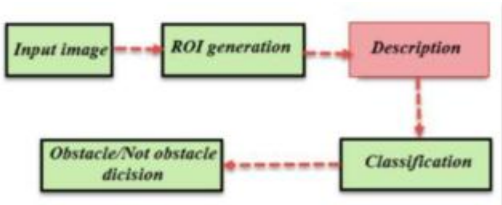

Fig.1 Obstacle detection chain

The remaining of this paper is organized as follows: in the second section, we will summarize some related works. In the third section, we will briefly describe the computation steps of the standard HOG descriptor [7]. The proposed customized HOG will be presented and discussed in Section 4. Experimental results for vehicle detection are given and discussed in section 5.

II. Related work

For the last few years, several studies related to the image description have been investigated. Dalal and Triggs [7] have invented a powerful human individual’s descriptor named HOG. Through the high performance given by this pedestrian descriptor, some other researches have been developed to take its advantages and extracted features of other objects like face, head, bicycle, car, etc. Since we are interested in vehicle’s recognition system, we will only mention some works handling vehicle detection.

A typical preceding system for vehicle detection using a standard HOG descriptor and SVM classifier has been presented in [8,9]. Arróspide et al. in [10] have proposed a HOG-like gradient-based descriptor for vehicle verification with an exploitation of the known rectangular shape of vehicle rears. To detect vehicles in videos, a combination of Haar features and HOG features have been presented by Youpan Hu et al. in [11]. The authors have expressed that their method can classify and detect the vehicles in multi-orientations with good classification results. The same procedure has proposed in [12] by Pablo Negri et al. but with a comparative study between the Haar-like features, HOG features and their fusion. The results show that the fusion combines the

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advantages of the two first detectors. Known that the standard parameters of HOG are optimized for human recognition, a re-optimization of HOG parameters for vehicle detection has been presented by Ballesteros et al. in [13]. They have tested various combinations in their experiments, the results show that; [-π π] as orientation range, (η=4) as the number of cell, (β=16) as the number of orientation bins and a nonlinear kernels on SVMs are the most suitable choice for vehicle detection.

In this paper, we are interested in analyzing the HOG descriptor model presented by Dalal and Triggs [7]. Based on our previous work [14], a new histograms computational method is proposed to customize the standard HOG for vehicle detection. At that point, a comparison between our approach and other works will be discussed.

III. Overview of HOG feature descriptor

The histograms of oriented gradients is a local descriptor. Such algorithm describes the gradient orientation in small areas of an image, and then it collects the information obtained from all regions into a single vector. Dalal and Triggs in [7] have partitioned the image into regions that are called cells; each cell contains 8x8 pixels. So the methodology of the HOG descriptor is to describe firstly each cell separately, by computing his HOG features vector (vector contains 9 bins). To increase immunity against light variations and lighting conditions, they have normalized all 2x2 cells (this set was called a block) to an L2-norm:

$$V \rightarrow \frac{v}{\sqrt{\|v\|_2^2 + \varepsilon^2}} \tag{1}$$

Where, V is the normalized vector, v is the non-normalized vector and ε is a very small constant.

The final HOG vector is the collection of all normalized vectors of each block with an overlapping of 50% per cell. Considering a detect window of 64x128 pixels, which contains 7x15 blocks (see Fig 2). The assembly of normalized vectors for all blocks into a single 1-D vector gives then 3780 components (36 x 7 x 15 = 3780).

1. *Gradients and oriented gradients calculation*

In the literature, several methods for gradient computation have been presented. According to the experimentation in [7], the use of a simple derivative mask centered [-1, 0, 1] turns out to be the best results. This mechanism is achieved by applying the horizontal and vertical gradient computation, as well as the magnitude computation. Equations are as follows:

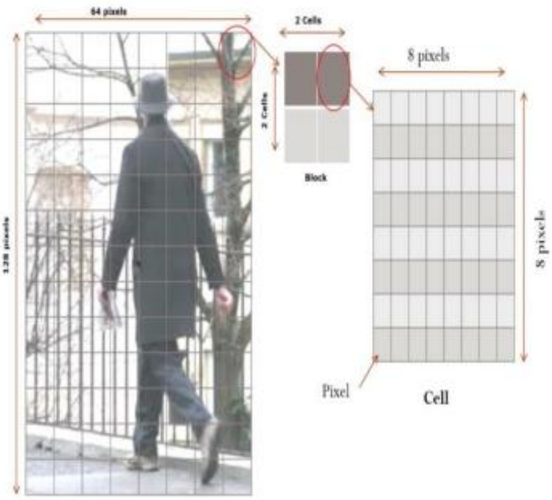

Figure. 2 Overview of HOG features configuration: window, blocks and cells

$$dx(x, y) = [-1, 0, 1] * I(x, y) \tag{2}$$

$$dy(x, y) = [-1, 0, 1]' * I(x, y) \tag{3}$$

$$M(x, y) = \sqrt{dx(x, y)^2 + dy(x, y)^2} \tag{4}$$

Where, dx(x,y), dy(x,y) and M(x,y) represent respectively the horizontal gradient, the vertical gradient and the magnitude of pixel.

The gradient orientation in the pixel I(x,y) is given by the following equation:

$$\Theta = \arctan\left(\frac{dx(x, y)}{dy(x, y)}\right) \tag{5}$$

2. *Orientation binning*

The second step of calculation consists in creating the cell histograms. In statistics, a histogram is a graph to show the distribution of a continuous variable. To handle the case of HOG, the histograms show the partition of the orientated gradients elements over local spatial regions that called cells. Each pixel within the cell provides a weighted vote for an orientation-based histogram channel, built on the values found in the gradient computation. The histogram channels are equally spread over [0 π] plan or [0 2π] plan, depending on whether the gradient is “unsigned” or “signed”. Dalal and Triggs, in their experiments, found that unsigned gradients used in conjunction with 9 histogram channels performed the best results. As for the vote weight, pixel contribution can be the gradient magnitude itself, or the square root or square of the gradient magnitude.

3. *SVM classifier*

Typically, obstacle detection systems have two parts: a training phase in which features are extracted on a standard dataset, and a decision phase in which the

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obtained features vectors are input to a classification system. Using the classifier in the detection system, we can determine the common characteristics of the examples that belong to the same class in order to subsequently recognize the class of a new unknown sample. SVM classifier is an algorithm for a binary classification. Such algorithm builds an optimal hyper-plane to separate the examples of two different classes during the learning phase in a high-dimensional space [15, 16]. Thus, the decision is taken using the previously constructed hyper-plane.

Considering the following set of learning:

$\{X_k, Y_k\}$: X_k are the HOG vectors and $Y_k \in \{-1,1\}$ are the class labels.

Initially, the method involves the transformation of in a larger space with the function (ϕ). Then it tries to find a decision function, which is given by:

$$f(x) = w^* \varphi(x) + b \qquad (6)$$

$f(x)$ is optimal in the sense that it maximizes the distance between the nearest point and the hyper-plane. The class label of the X vector is then obtained by considering the sign of f(x). Solving the optimization problem is obtained by using the following equation:

$$\underset{w\xi}{Min} \frac{1}{2}\|w\|^2 + c\sum_{k=1}^{m} \xi_k . \qquad (7)$$

Enhancing the SVM is the selection of the suitable kernel function from; linear, RBF, polynomial and quadratic. In our experiments, we will use the linear SVM as our binary classifier due to its faster computation.

IV. Improved HOG approach

1. *Re-optimizing the HOG parameters for vehicle detection:*

The main goal of our approach is to increase the accuracy of the road-obstacle detection system. In our previous study [14], we have presented an improvement for the pedestrian detection system. In this work, we are interested in the vehicle detection system. In an image, pedestrian and car have various different characteristics. The HOG descriptor is primarily built for pedestrian detection, Dalal and Triggs [7] have optimized its parameters to get the best results for the human detection. Here, we need to re-optimize several parameters of the standard HOG descriptor to get the best results for the car detection. Then we add the process of our approach.

Primary, most of the vehicles have rectangular shapes, and they have a largest size then a pedestrian, that explicate the choice of (128x128) pixels per window in the learning system. Second, in our experiments, changing the number of pixels per cell, the number of cells per blocks and the overlapping ratio does not affect the system's performance.

Consequently, we will keep the same parameter's values proposed in the standard HOG, that turn out to be effective to express the car features in images. Finally, vertical orientations for a car are characterized by an acute and accurate angle, which does not change within its movement at variance with the pedestrians. That leads to minimize the scale of bins by increasing its number in [0 π] plan. The simulation results for different values of bin's number (labeled NB in the figure) are shown in Fig 4.

The simulation produces the best result for 36 bins, but it represents the most complex and greedy simulation: resource intensive, memory consuming, execution time... In the following, we will apply our approach for a number of bins equal to 18; first, in order to save simulations time, and second to show the efficiency of our approach since this case represents the lower performance for the true positive rate.

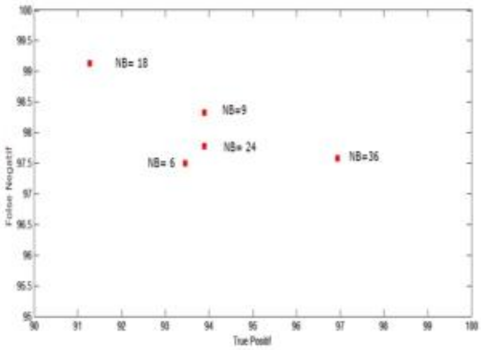

Fig. 3 Recognition rate according to the number of bins in the histograms

2. *Database*

To build a vehicle recognition system in the conventional supervised learning, the positive training examples consist of vehicle images, and the negative training examples consist of random non-vehicles images. The datasets used in our system are INRIA cars [17], MIT cars [18] and Markus cars [19] as positive examples and not pedestrian INRIA datasets as negative examples. Fig 3 shows some positive and negative examples.

(a)

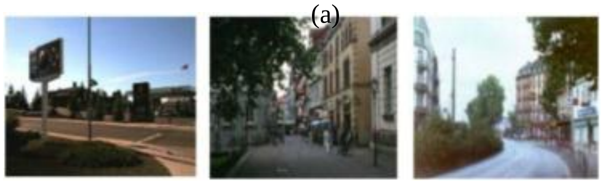

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Fig. 4 Image examples from datasets: (a) Negative examples, (b) Positive examples.

We manually delete the images for not pedestrian examples that contain cars in the goal to use them as negative examples for learning. We have obtained 988 car images with their reflections (1 976 samples in total) as positive examples and 4 236 samples extracted from 1 059 non-car images as negative examples. 1/3 of each database was intended for test and 2/3 was intended for learning the system.

3. Improved HOG approach

The proposed approach consists of three phases. First, we modified the computational method of the standard HOG features to get an average HOG features vector for each image in the dataset. Second, we apply a new process to extract the bins that characterize more the vehicle features from a side; we will call it the most significant bins. Finally, we amplify the extracted bins in the new customized HOG algorithm that will be included in the main chain of the vision system. Further explications are exhibited below:

We modified computational method of the HOG vector at the end to extract the histograms that characterize more particularly the desired object. This is achieved by adding all vectors obtained by cell instead the concatenation as in the original HOG algorithm. This technique gives an average vector that contains only 9 components instead of 3780.

Taking into account the large inter-variety between vehicles, we must now, generalize this vector through averaging it in the whole database that contains n vehicle samples. The same procedure was performed for the calculation of the average vector for the negative examples (not vehicle images in all training and test negative examples).

By now, we have two main vectors that define vehicle images and random images through 18 bins for each one. Subsequently, we calculated the difference between the bins values of the two histograms in order to extract the most significant bins in vehicle images. The last step is to sweep the amplification factor for the selected bins at the end to get the best recognition rate for the car detection.

V. Experimental results

1. Extraction of significant bins

As shown in Fig.5, the subtraction between the two mean vectors of the negative and positive examples for the car datasets used in our experiments (INRIA, MIT, MARKUS) gives four bins (2,7,15 and 17) whose values are reversed compared to the others bins. As a matter of fact, these bins have larger gradients orientation density in a car image than a random image in traffic environments. On the other hand, the bins number (6, 10, and 14) represent the highest values in this histogram. These bins encode the least frequent oriented gradients for a car images.

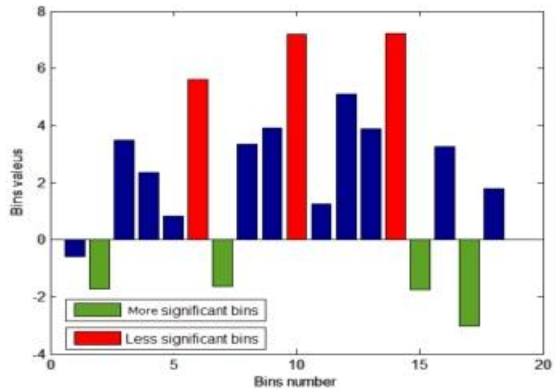

Fig. 5 Most significant bins for a car features extraction based on 18 bins.

2. Select the amplification factor

sign
(see

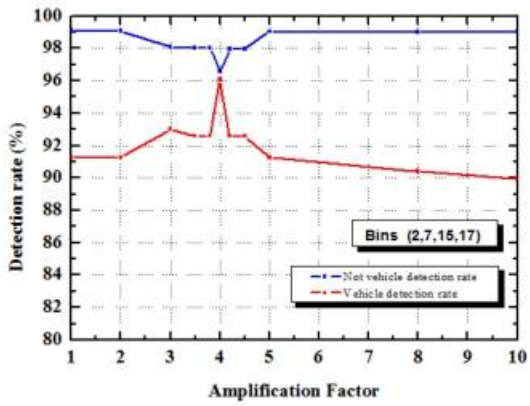

Fig. 6 Detection rate with an amplification process for bins (2,7,15,17)

The amplification of bins 2,7,15 and 17 has achieved the best a recognition rate 98.25% for the vehicle detection and 95.4308 for the non-vehicle recognition system. The amplification factor getting the highest rate is equal to 4.

A comparative study between our results with others (presented in Table 1), shows that the proposed approach

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outperforms recent works. However, we cannot rely on this comparison because we do not share the same database, seeing that a growing number of on-road vehicle studies are reporting results from private video datasets.

TABLE 1: COMPARISON OF EXPERIMENTAL RESULTS

Methods	True positive examples rate	True negative examples rate
[10] HOG-Like Gradient	92,48%	--
[11] Haar features and HOG features	97.2%	96.8%
[9] HOG	96.87%	97,33 %
[17] HOG/HCT	85.2% %	--
This work	**98.2533%**	**95.4308**

VI. Conclusion

Performance evaluations show that the proposed approach can have significant enhancement, to characterize vehicle compared to the standard approach. The main contribution of this approach is to extract, then amplify the most significant bins that describe particularly the desired object. This technique presents a potential solution to the emerging problems related to the obstacle detection for ADAS. Future research works will focus on real-time vehicles detection on Field Programmable Gate Arrays (FPGAs) using the customizing HOG descriptor.

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