Moving Car Detection using HOG features

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Abstract— Vision is the most powerful sense of the five human senses. This paper proposes real-time monocular-vision based techniques for the multiple car detection. Car detection system should minimize driving difficulties in various conditions, like in sleeping, busy in communication devices etc., thereby reducing traffic accidents. Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) are used in this work. SVM is the classification method. HOG will extract the features of given frames extracted by video and that important features will be given to the SVM. Before that we have to give training dataset to SVM to train it, because SVM is supervised learning algorithm. According to training it will classify data and accordingly present or absent of car is decided. Simulation results are presented for different images, which show accuracy of suggested approach.

Key words: Car Detection, Histogram of Oriented Gradients, Support Vector Machine, Hard Negative Mining

I. INTRODUCTION

All around the world tens of thousands of people die on the road due to accidents involving more than one vehicle each year.[6] According to statics [1] published in 2012 about traffic safety in the USA, a significant percentage of all traffic accidents involving rear-end crashes. The cited study considers the 19 categories of crashes such as rear-end, guard-rail, head-on, crash with animal, crash with pedestrians, or rollover, plus their rate of contribution in the terms of total number of accidents, fatalities, injuries and property loss.

By maintaining early vehicle detection and warning for that vehicle, it is possible to provide more time to distracted driver to take an appropriate action to resolve that driving conflicts and consequently to decrease possibilities of rear-end crashes [2].

Moving object detection from video frame is one of the most active areas of research in the world. Research and development efforts in advanced sensing of front vehicles, environmental perception and smart driver assistance system that help to save lives and reduce on-road fatalities [6].

Vehicle detection system plays important role in many applications, such as driver assistance system, automatic parking systems and self-guided vehicle. But vision based systems are mainly used in vehicle detection.

There are different papers referred, in which they are using different methods as Minkyu, Wonju, Changyong and Mignon uses HOG with Total Error Rate minimization using Reduced Model TER-RM classifier [1]. Mahdi, Mutsuhiro uses haar fetures for vehicle detection [2]. Olga, Victor and pushmeet developed hough transform based detection [3]. Mahdi Giseok Kim and Jae-Soo Cho present method uses the combination of multiple vehicle features [4].

In this paper we suggest a monocular vision based system to detect vehicles from road images taken by a camera inside from a moving car. Because car accidents normally occur in an instant, the system processing time must be as fast as possible to recognize vehicles on the road and that's why prevent car accidents.

There are different algorithms used to detect vehicle like hough transforms, partial least square, haar features, histogram of oriented gradients etc. In this work we used Histogram of Oriented Gradients for feature extraction, and Support Vector Machine for the feature classification.

HOG provides important features to SVM and SVM will classify it. For example, we given a set of training data, each marked with a one of any two categories an SVM training algorithm builds a model that assigns new examples into one category or the other category. SVM works better when classification gap is clear and wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

II. LITERATURE SURVEY

Paper presented by Minkyu Cheon, Wonju Lee, Changyong Yoon, and Mignon Park [1] that is proposed to improve vehicle detection in video surveillance the detection process generally occurs in following steps: object detection and object classification. They are using Histogram of Oriented Gradients symmetry vectors and Total Error Rate minimization using Reduced Model (TER-RM) classifier. The most frequent errors of this approach are due to inaccurate hypotheses generation.

Paper presented by Mahdi Rezaei, Mutsuhiro Terauchi and Reinhard Klette [2] proposes real-time monocular-vision based techniques for simultaneous vehicle detection and inter-vehicle distance estimation, in which the performance and robustness of the system remain competitive, even for highly challenging benchmark datasets. This paper develops a collision warning system by detecting vehicles ahead, and by identifying safety distances to assist a distracted driver, prior to occurrence of an imminent crash. They introduce adaptive global Haar-like features for vehicle detection, tail-light segmentation, inter-vehicle distance estimation, as well as an efficient single-sensor multi-feature fusion technique to enhance the accuracy and robustness of their algorithm.

Paper presented by Olga Barinova, Victor Lempitsky, and Pushmeet Kholi [3] developed a new probabilistic framework for object detection which is related to the Hough transform. It shares the simplicity and wide applicability of the Hough transform but, at the same time, bypasses the problem of multiple peak identification in Hough images and permits detection of multiple objects without invoking nonmaximum suppression heuristics. But Hough transforms works only for line and pedestrian detection, and in vehicle detection it needs to detect edges of the given images.

Mahdi Giseok Kim and Jae-Soo Cho [4] proposed a robust real-time vehicle detection and inter-vehicle distance estimation algorithm for vision-based driving assistance system. The proposed vehicle detection method uses the combination of multiple vehicle features, which are the usual

Haar-like intensity features of car-rear shadows and additional Haar-like edge features. And, after analyzing two inter vehicle distance estimation methods: the vehicle position based and the vehicle width based. But the proposed method is only applicable to the day time.

Sayanan Sivaraman, and Mohan Manubhai Trivedi [6] provided a review of the literature addressing on-road vehicle detection, vehicle tracking, and behaviour analysis using vision. Included in this treatment of vehicle detection is the treatment of camera placement, night time algorithms, sensor-fusion strategies, and real-time architecture. They provide information on the state of the art, detail common performance metrics and benchmarks.

III. BACKGROUND

A. *Histogram of Oriented Gradient*

HOG features have been introduced by Navneet Dalal and Bill Triggs [10], who have developed and tested several variants of HOG descriptors, with differing spatial organization, gradient computation and normalization methods. HOG descriptors are feature descriptors used in computer vision and image processing for the purpose of object detection. This technique counts occurrences of gradient orientation in localized portions of an image.

Thought behind the HOG descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients and edge directions. The whole image is divided into small connected regions, which are called as cells, and for the pixels within each cell, a histogram of gradient directions are calculated [10].

The aim of HOG is to describe an image with a local oriented gradient histogram. These histograms represent occurrences of a specific gradient orientation in local parts of the image. The HOG can be calculated in a three-step sequence: 1) gradient computation; 2) orientation binning; and 3) histogram generation [6].

1) *Gradient Computation:*

The first step of calculation is the computation of the gradient values. The most common method is to apply the 1D centered point discrete derivative mask in both the horizontal and vertical directions. Specifically, this method requires filtering the gray scale image with the following filter kernels:

$D_x = [-1\ 0\ 1]$ and $D_y = [-1\ 0\ 1]^T$

Either signed or unsigned gradient can be used; in this case, we use a signed gradient whose values range from $-\pi$ to π.

So, being given an image I, we obtain the x and y derivatives using convolution operation:

$I_x = I * D_x$ and $I_y = I * D_y$

The magnitude of the gradient is $|G| = \sqrt{Ix^2 + Iy^2}$

The orientation of gradient is given by $\theta = \tan^{-1}(I_y/I_x)$

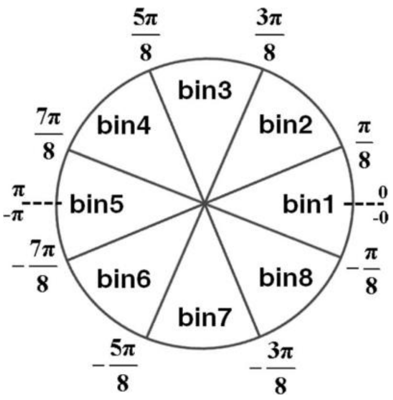


Fig. 1: Orientation range for each bin for 8-D HOG [6]

2) *Orientation Binning:*

The second step of calculation involves creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation.

The cells themselves are rectangular and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is "unsigned" or "signed" [10].

From the papers found that unsigned gradients used in conjunction with 9 histogram channels performed best in their experiments. As for the vote weight, pixel contribution can be the gradient magnitude itself, or the square root or square of the gradient magnitude. Fig.1 and Table 1 shows orientation range for each bin of 8-D HOG.

For orientation binning, the image should be divided into blocks of predefined size.

Bin	Range
1	$\frac{-1}{8}\pi \le \theta < \frac{1}{8}\pi$
2	$\frac{1}{8}\pi \le \theta < \frac{3}{8}\pi$
3	$\frac{3}{8}\pi \le \theta < \frac{5}{8}\pi$
4	$\frac{5}{8}\pi \le \theta < \frac{7}{8}\pi$
5	$\frac{7}{8}\pi \le \theta \le \pi, -\pi < \theta - \frac{7}{8}\pi$
6	$\frac{-7}{8}\pi \le \theta < -\frac{5}{8}\pi$
7	$\frac{-5}{8}\pi \le \theta < -\frac{3}{8}\pi$
8	$\frac{-3}{8}\pi \le \theta < -\frac{1}{8}\pi$

Table 1. Orientation Range of Each Bin For 8-D HOG

Further, for histogram generation, the range of each bin is determined. For example, if the signed gradient is divided into six bins with the same range, then the range of each bin is 60° ($\pi/3$ rad).

3) *Histogram Generation:*

In the histogram generation step, we impose values on the histogram of each block. According to the orientation of the gradient, the magnitude of the gradient is accumulated in the bin of the histogram [10].

In our proposed vehicle detection system, the size of the data set is 64 $\times$ 64 pixels, where the range of each bin is 45°. Figure 1 shows the orientation ranges of each bin for 8-D HOG.

B. Support Vector Machine Classifier

The original SVM algorithm was invented by Vladimir N. Vapnik and Alexey Ya. Chervonenkis. Support Vector Machines (SVM) has recently shown their ability in pattern recognition and classification. The idea of Support Vector Machines is to map the input data into a high dimensional feature space.

In machine learning, Support Vector Machines are supervised learning algorithms. There are two types of machine learning algorithms: Supervised learning and unsupervised learning. SVM is supervised learning because it needs training dataset to train itself.

There are two types of SVM: Linear SVM and Non-linear SVM. We are using linear SVM in this work. More formally, SVM constructs a hyper plane or set of hyper planes in high or infinite dimensional feature space which can be used for classification, regression, or the other tasks.

Data set is providing to SVM to classify. If we provide huge data set to classifier, it's become difficult for classifier to classify the data set properly and also the procedure become quite heavy. If we provide only important features data set to the classifier then classification results improve. Histogram of Oriented Gradients will extract the unique features and will provide the feature set to the SVM to classify data and it thus it will improve the discrimination ability of a classifier.

SVM develops hyper plane that classifies data. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training-data point of any class, since in general the larger the margin the lower the generalization error of the classifier.

Classifying data is a common task in machine learning. Suppose there is one data point, and we want to know that in which category it will fall. There are various classifiers available which classifies data. But the good classifier is that which classifies data with maximum margin hyper plane.

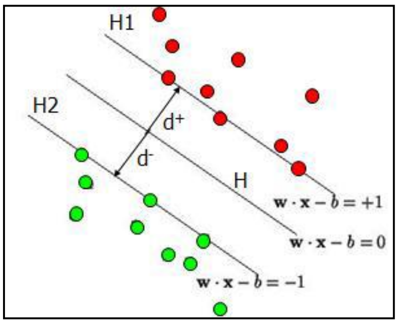


Fig. 2: Support Vector Machine Hyper plane [11]

H1 and H2 are the planes:

H1: **xi•w**+b = +1

H2: **xi•w**+b = -1

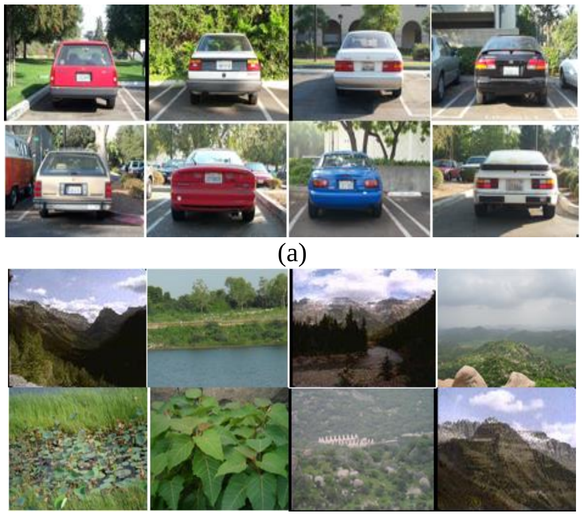
The points on the planes H1 and H2 are the Support Vectors:

$\{x_i : |w^T x_i + b| = 1\}$

d^+ = the shortest distance to the closest positive point

d^- = the shortest distance to the closest negative point

The margin of a separating hyperplane is $d^+ + d^-$.



(a)

(b)

Fig. 3: (a) positive training data, (b) negative training data

SVM is a classifier, so it needs two datasets to classify it. In this topic there is one positive and one negative dataset is provided to the Support Vector Machine. SVM will make two groups and give them two labels as 1 and -1 or 0 and 1 whatever you want. SVM will divide whole dataset in these two groups. Support Vector Machine will do this whole process after train it, that's why it is supervised algorithm. Training dataset for positive (car images) is shown in fig. 3(a) and training dataset for negative images is shown in fig. 3(b).

IV. Proposed Work

In proposed work we use HOG feature descriptor for feature extraction. HOG will extract important features of the video frames. SVM is the supervised learning algorithm used for classification. According to training data it will classify images of vehicles and non vehicles. To improve SVM accuracy, the SVM can be trained multiple times using any false detection as mining for hard negative, this can be potentially reduce false positive rate and increasing accuracy.

Step of proposed work:

1) Input the video frame
2) Extraction of features using HOG descriptor
3) Give training data to SVM
4) Use SVM to classify the images
5) After classify the image perform hard negative mining
6) Result evaluation

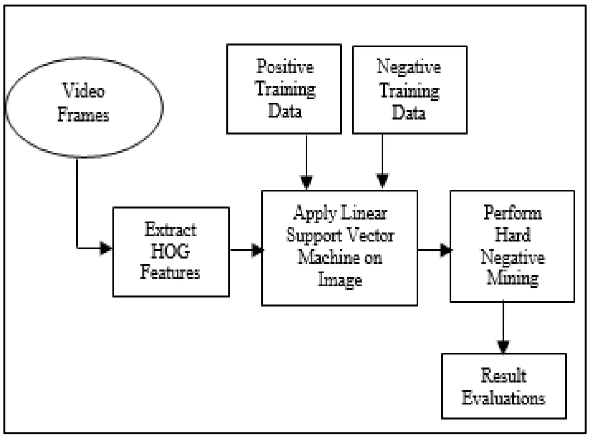


Fig. 4: Process of vehicle detection

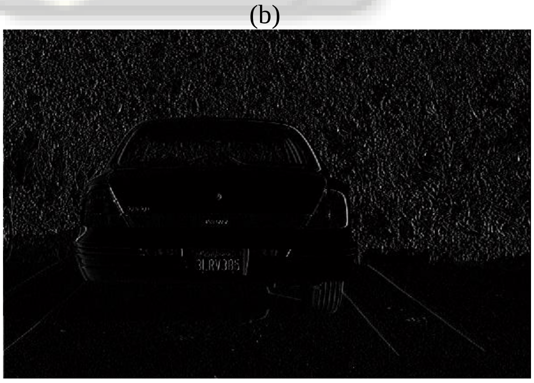
V. RESULT AND DISCUSSION

Simulation results for HOG are shown below. In below given images, fig.5 (a) is the RGB image of the car. For the further processing RGB image is converted into gray scale image. So fig.5 (b) is the gray scale image.

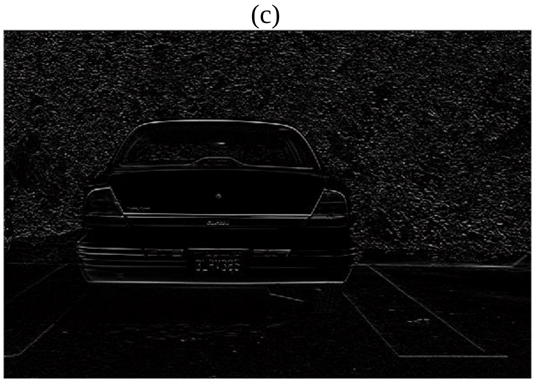
According to theory of HOG, after applying 1-D filters to gray scale image it will give Y gradient image and after applying transpose it will give Y gradient images. Fig.5 (c) and (d) shows X and Y gradient image. After calculating magnitude and angles it gives fig.5 (e) and (f). And extracted features of car image which is given as input is shown in fig.5 (g).

(a)

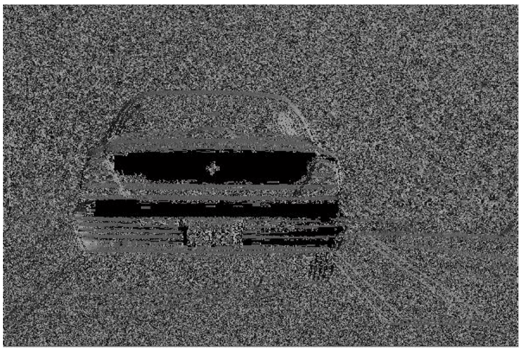
(b)



(c)

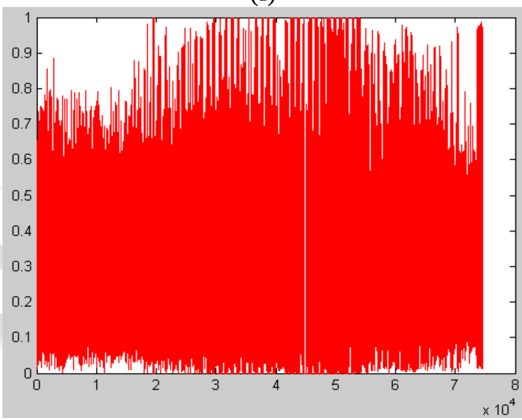


(d)



(e)

(f)



(g)

Fig. 5: Simulation results of Histogram of Oriented Gradients (a) RGB Image, (b) Gray Image, (c) Extracted X Gradient, (d) Extracted Y Features, (e) Extracted Angles, (f) Extracted Magnitudes, (g) Extracted Features

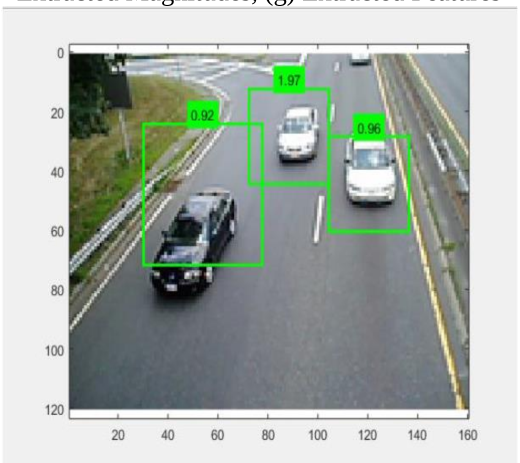


Fig. 6: Simulation Results

Detection of moving car is done using HOG and SVM, simulation results of moving car detection are shown in fig.6.

Fig. 7: Half visible cars

This algorithm is also shows correct results for half visible cars as shown in the above fig.7.

VI. CONCLUSION

In this paper, we suggest a monocular vision based vehicle detection for the driver assistance system. This vehicle detection method uses HOG which is feature descriptor and SVM which is data classifier. This application is used to reduce the accident rate. Vehicle detection is used in practice and it is useful in routine life. Traffic hazards are reduced by applying the importance value of data, i.e., detected locations to the learning method. Various experimental results show that the suggested method is practically applicable to the driver alarm system for driver safety.

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