Comparison of Forward Vehicle Detection Using Haar-like features and Histograms of Oriented Gradients (HOG) Technique for Feature Extraction in Cascade Classifier

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***Abstract*— This paper present an algorithm development of vehicle detection system using image processing technique and comparison of the detection performance between two features extractor. The main focus is to implement the vehicle detection system using the on-board camera installed on host vehicle that records the moving road environment instead of using a static camera fixed in certain locations. In this paper, Cascade classifier is trained with image dataset of positive images and negative images. The positive images consist of rear area of the vehicle and negative image consist of road scene background. Two features extractor, Haar-like features and histograms of oriented gradients (HOG) are used for comparison in this system. The image dataset for training in both feature extractions are fixed in dimension. In comparison, the accuracy and execution time are studied based on its detection performance. Both features performed well in detection accuracy, whilst the results indicate that the Haar-like features execution time is 26% faster than by using HOG feature.**

***Index Terms*— Cascade classifier; Haar-like; HOG; Vehicle detection.**

I. INTRODUCTION

Vehicle detection system is one of the important component in autonomous driving for intelligence support system in traffic monitoring and driving assistance [1]. The design aimed on human computer interaction in term of visual for human understanding [2] of the road surrounding. There are numbers range of on-board sensors used for vehicle detection that includes radar [3], LIDAR [4], [5], and computer visions [6]–[8]. Vision-based research on vehicle detection is raising many interests which progressing rapidly in recent years. Since camera technology are well improved in recent development, low cost camera in high specification with the ability to capture and records images in high quality are easily found in the market at low cost. Therefore, implementation of image processing technique for detection system is at advantage [6].

In this paper, an image processing technique is proposed to develop a vehicle detection system. In this development, on-board camera is installed in host vehicle. The host vehicle records highway scene around Malaysia under normal driving condition, aiming to use the video to detect the forward vehicles presence in the video. By using open and moving environment, visions capable of measuring the number of vehicles, the traffic flow, speed, even driving characteristic for studies and many more [9]. Therefore, the main goal of this paper is to detect vehicle on rear part of the vehicle seen clearly in the forward video collections.

Vision method can be categorized into two groups, static and dynamic. In the studies of static method, the camera is placed at fixed position for monitoring the road traffic. Studies from [10], implement a video sequence from the roadside CCTV in their studies. By static positioned camera, the extraction of foreground and background are advantageous as the scene are not constantly changing and background subtraction method can be implemented to reduce interference such as road markings, road sign and the trees. Furthermore, [11] uses wide area motion imagery (WAMI) for its vehicle detection system. WAMI data is an aerial imagery consists of the global coverage image of the road scene. The drawbacks of using this imagery are the small number of pixels on the target object and also low frame rate.

In dynamic method, the camera is installed in host vehicle and the road environment is recorded. It is dynamic since the motion of the surrounding objects and background are in motion. Studies by [12], uses the motion properties and behavior of road scenes in spatiotemporal image for their vehicle identification system. To distinguish the background motion, its camera ego-motion and distance are studied. The vehicles ahead are detected as their motions are moving in the same direction of their car. Optical flow methods used by [13] , extract feature point from edge image using the Canny operator. Its optical flow feature points set information are calculated using Lucas-Kanade optical flow pyramid model. Vehicle pattern based on its feature point are identified in order to efficiently detect from the complex and dynamic background since the video are captured by a camera on a moving car.

Based from the analysis above, this paper produces Cascade Classifier ensemble training for vehicle detection in comparison from using Haar-like features and also histograms of oriented gradients (HOG) feature extractor. This classifier is common in object detection and performed well in especially facial detection and recognition studies [14], [15], pedestrian detection [16]. Haar-like features are said to be insensitive to illumination [17] thus robust for the road environment luminance that constantly changes due to the weather. Nonetheless, for the HOG feature extractor is known as a robust method for feature descriptor in the object detection implementation [18]. Provided that, both feature extractors are implemented into training operation by Cascade Classifier using the same dataset prepared. The performances of both detectors are compared to choose which method is better for vehicle detection system. The algorithm development is described in the next section and with that case the results are discussed.

II. ALGORITHM DEVELOPMENT

The overall flow of algorithm development in vehicle detection system using image processing technique are illustrated in the flow diagram Figure 1.

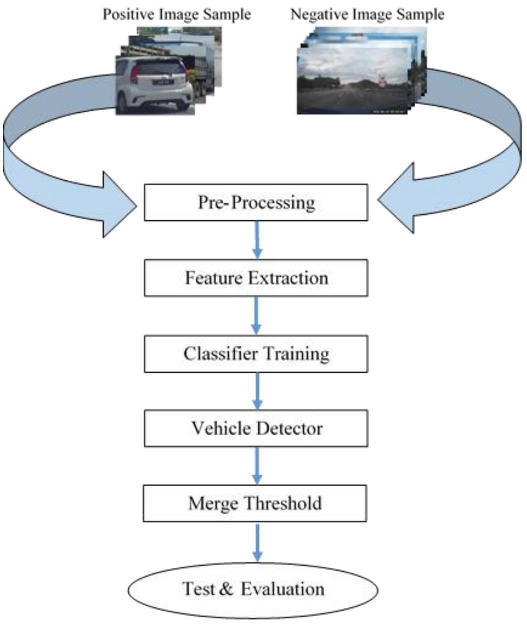


Figure 1: Overall flow of the development

Two collections of image dataset; positive images and negative images are prepared and collected from the video frame recorded by the on-board camera installed in host vehicle. The positive images set are the rear area feature of vehicle in highways to achieve the forward vehicles detection whereas the negative images are the set of road highways background that the vehicle are not visible or present. Next, all the image dataset pre-processed which leads to gray scaling the images and increasing the image contrast for feature enhancement.

Haar-like features and Histogram of Oriented Gradient (HOG) are used to extract the image dataset features. Both technique are used for performance comparisons in which between the two features can perform well in vehicle detection under dynamic scene. Both feature extractor undergone cascade classifier training to generate vehicle detector system. In the end, two system objects are generated from the training of the image dataset of two features; Haar-like vehicle detector and HOG vehicle detector.

Merge threshold algorithm are used to reduce multiple detection box overlap from occurring. Moreover, it also added to reduce false detection of surrounding objects on the highways scenes such as road markings and sign board.

In the end, vehicle detector for both features type are tested on video recorded by the host vehicle. Forward vehicle detection performance are analyze to determine which features perform best as a vehicle detector system.

A. Image Dataset Preparation

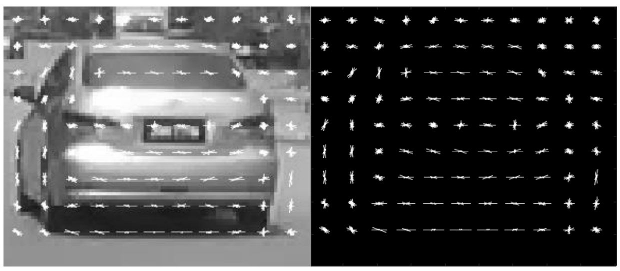
The image dataset of positive and negative image are prepared using image frame obtained from the video recorded by host vehicle. The positive image dataset consist images of rear area of the forward vehicle, with total of 600 vehicle images consist of cars, lorry and bus vehicle type in dimension of 80x80 pixel. On the other hand, total of 2000 negative images are the road background that do not in the presence of vehicle, which are the object of interest in the detection.

Image enhancement is an important process to improve the features appearance [19]. Therefore, under pre-processing process, undergone colour conversion from RGB to grayscale and later with contrast adjustment for highlighting more of vehicle rear area features. Rescaling of the image are executed for positive image dataset, ready for feature extractions.

B. Feature Extraction

In image dataset feature extraction, Haar-like features and HOG features are applied to the positive image dataset. Both feature extractor are implemented for performance comparisons to find suitable features in the vehicle detection system. The process of feature extraction involves in assigning vector descriptor to the object around its point feature in the image where in this case the rear side of the vehicle.

HOG feature vector is visualized as shown in Figure 2, where the HOG vector is on the grayscale image of the rear side of the vehicle. Figure 2 (b) is the outline of the vehicle feature extracted by HOG vector. The outline shows the direction of the vector based on the vehicle feature. The theory of the vector magnitude is that to obtain the feature of the object, orientation of the gradients in each pixel of the image region needs to be calculated [20].



(a) (b)

Figure 2: HOG feature vector

Haar-like features use rectangle wavelet as shown in Figure 3, in which the feature is defined by the rectangular wavelet [21] and a threshold value. Using the vehicle image dataset, intensity of dark region and bright region are calculated and its total is compared to find the positive example and negative example. If dark region intensity is greater than the bright region by the threshold then it is positive example and vice versa of the condition determines that it is a negative example [22].

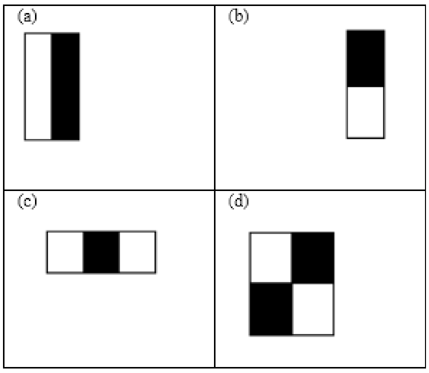


Figure 3: Rectangular wavelet

After the process of features extraction on the image dataset, Haar-like feature dataset and HOG feature dataset are ready for cascade classifier training for developing the vehicle system detector.

C. Cascade Classifier Training

In theory, Cascade classifier is a cascading multistage of ensemble learning that uses the output from the previous stage of classifier onto the next classifier in the cascade as shown in Figure 4. The system object detector output is the detector used in the vehicle detection system to detect vehicle in road video captured by the on-board camera.

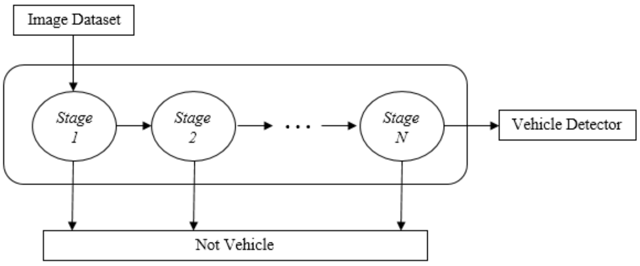


Figure 4: Cascade Classifier

Using the image dataset with Haar-like features and HOG features extracted, both features are trained separately into the cascade classifier. Both image dataset feature type are trained with the same negative image dataset. A total of N = 14 stages in classifier training are executed to obtain the vehicle detector for each feature type. The vehicle detector for each feature output trained are tested using 15 Malaysia highway road videos to test detection performance of the forward vehicle in the video sequence.

D. Merge Threshold

There are problems occurred during vehicle detection test on road highway scene video. The problem is that multiple bounding boxes are overlapping onto the detected vehicle. Other than that, even with low false alarm rate set for each classifier stage, false detection does occur regularly thus, increasing the false detection rate.

To overcome this problem, merge threshold is applied to the vehicle detector in order for the detected vehicles are labelled with only one detection bounding box around it. Therefore, groups of the detection bounding box overlapped onto the vehicle that meet the threshold value conditions are merged into producing one single detection bounding box.

Figure 5: Merge Threshold on Vehicle Detector

Figure 5 (a) - (c) shows the result of merge threshold implementation for Haar-like vehicle detector (blue) and HOG vehicle detector (red) in side by side for comparison. The result aim to show the difference of the detection bounding box appearance when the merge threshold is applied and varied on different values.

The variation of merge threshold value from the figure illustrate detection bounding box behavior. From the observation, we can see that false detection occurred and overlap of bounding box happens when merge threshold is 0 as shown in Figure 5 (a). The system is tested by adding merge threshold with increment by one starting with 1 and incremented until the value is 8 with Figure 5 (b) shows the result in no false detection and overlapping bounding box. However, if the merge threshold value gets too high, misdetection can be happened as in Figure 5 (c). In the end, merge threshold value of 8 are used in the vehicle detection system for both feature type.

III. RESULT AND DISCUSSION

Two vehicle detector systems; Haar-like features and HOG vehicle detection system is evaluated and analyzed using same video sequence that are recorded using an on-board vehicle camera. The video consists of road traffic around Malaysia highways. Both system detectors are compared by analyzing its detection accuracy that includes the true positive rate, Tp in equation (1), and false detection rate, Fd in equation (2). Other crucial comparison is the execution time for both vehicle detection systems using Et in equation (3).

$$Tp = \frac{Detected\ vehicle}{Total\ number\ of\ vehicle} \quad (1)$$

$$Fd = \frac{False\ positives}{Detected\ vehicle + False\ positive} \quad (2)$$

$$Et = \frac{Execution\ time}{Video\ time\ frame} \quad (3)$$

Figure 6 (a) – (e) shows the detection results of the algorithm of both features Haar-like features and HOG. Figure labeled with blue bounding boxes are the detection by using Haar-like features algorithm, while figure labeled with red bounding box are the detection by using the HOG features algorithm of the vehicle.

The robustness of the detector system for both feature type using the same 15 video samples are tested and five of the video detection system results are shown in Figure 6. In Figure 6 (a), both systems successfully detected two vehicles presence at the scene and the billboard above did not cause a false detection. Unfortunately, in Figure 6 (b) false detection occurs on a HOG detection system when the side road billboard is falsely detected and misdetection of lorry happens while Haar-like features system detector manages detect all vehicle presence. Figure 6 (c) – (e), detection for both systems are spot on and no false or misdetection happens.

The detection results of both systems in total vehicle detected and false detection are listed in Table 1and the true positive rate, false detection rate and execution time using equation (1), (2), and (3) respectively are tabulated in Table 2.

Table 1
Detection results for both detector

Feature types	Vehicle Detected	False Detection
Haar-like	197	96
HOG	194	175

Table 2
True positive rate, false detection rate and execution time results

Feature types	True positive rate, Tp	False negative rate, Fn	Execution time, s
Haar-Like	0.98	0.33	3.09
HOG	0.96	0.47	5.27

Execution time are determined by calculating the processing time it take for each frame of the video to scan the whole image with the algorithm. The scanning time takes effect based on the processing time of each features to scan whole image to find the vehicle.

Figure 7: False Detection

(a) Curved road

(b) Two lanes

(c) Three lanes

(d) During road construction

(e) Two lanes

Figure 6: Vehicle Detection Comparison between Haar-Like and HOG features

Figure 7 shows the example of false detection that occurs from both systems. Since the opposite direction vehicle have almost the same features of the rear area of vehicle the system detector assumes that those are the forward vehicle. This usually happen when the opposite vehicle is a van or lorry that have flat surface front face that resembles the rear are of a bus or lorry.

Based on the comparison of the detection system from Table 1 and

Table 2, Haar-like features for vehicle detection system proves better than of using HOG features for vehicle detection. Its detection rate is higher than HOG where it detected 197 vehicles from total of 202 vehicles rather by HOG with only 194 vehicles detected making it 2% less in true positive rate with Haar-like features detector. HOG features system also promotes high in false detection with 175 of false detection occurrences. Its total are higher than Haar-like with false detection of 96 occurrences. A high false detection may lead a big problem in terms of robustness of the system.

In other case, Haar-like feature detector is faster in its execution time. A major part in transition the system into real time is its need in faster process time. Therefore, with Haar-like features faster by 26% times more than HOG feature detector proves that Haar-like feature based detector system is the best technique for vehicle detection using cascade classifier.

IV. Conclusion

The development of vehicle detection system by image processing technique using two different feature extraction for performance comparison are proposed. The algorithm used Cascade classifier as main ensemble training by using the same positive and negative image dataset. Two vehicle detectors system are developed with both are distinguished by the use of feature extractor between Haar-like features and HOG features. The algorithm is tested and evaluated its performance using video data recorded by host vehicle using onboard camera. The performances of both vehicle detector are compared based on its true positive rate, false detection rate and execution time calculation and records. In the end, the studies proves that Haar-like features based are the best performance for vehicle detection using cascade classifier training rather than of using HOG features. The result shows that Haar-like based detector is 2 % more accurate in vehicle detections, 17.5 % less false detection than HOG based detector and also 26 % much faster in execution time.

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