On Road Vehicle Detection using Association Approach

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ABSTRACT
On road vehicle detection is an essential part of the Intelligent Vehicles and it is an important problem in the area of intelligent transportation systems, driven assistance systems and self-guided vehicles. The proposed algorithms should detect out all cars in realtime. Related to the driving direction, the cars can be classified into two types. Cars drive in the same direction as the intelligent vehicle and cars drive on the opposite direction of the intelligent vehicle. Due to the distinct features of these two types, we can use a fast approach so-called association is a modified version of the association approach [1] to detect both these directions. The proposed method is achieved in two main steps. The first one detects all obstacles from images. The second step is applied to each obstacle to verify if it is a vehicle or not by the mean of AdaBoost classifier. The modified Association approach has been applied to different images data and the results are satisfactory.

Keywords
Association, intelligent vehicle, vehicle detection, Optical Flow, AdaBoost, Haar filter, Temporal matching.

1. INTRODUCTION
Detection of road obstacles [1] [2] [3] [4] [5] [6] [7] is an essential part of the Intelligent Vehicles Systems and has many applications including platooning (i.e. vehicles travelling in high speed and close distances in highways), Stop&Go (similar that precedent situation, but at low speeds), and autonomous driving. A number of sensors embedded in Intelligent Vehicles to perform the vehicle detection task. These sensors can be classified into passive and active sensors. Known that active sensors are expensive and cause pollution to the environment, we propose to use passive sensors in our vehicle detection approach. The data we are going to process to achieve vehicle detection are images taken from a camera embedded in a moving car.

In the field of technical obstacle detected by vision system, two approaches existed: the first approach is unicameral approach that uses a single camera that consists of an image interpretation

with former knowledge of information about these obstacles. This information can be texture information [8], color [9], [10]. The second one is the stereo or multi-camera approach which is based on the variation map after matching primitives between different views of the sensor [11], [12] and [13]. Most of the detecting methods distinguish two basic steps: Hypothesis Generation (HG) and Hypothesis Verification (HV) [14].HG approaches are simple low level algorithm used to locate potential vehicle locations and can be classified in three categories; Knowledge-based methods which use symmetry of object, color, corners and edges; Stereo-vision-based methods which use two cameras; Motion-based Methods which track the motion of pixels between the consecutive frames [15]. The methods in the HV step are Template-based methods and Appearance methods. Template-based methods use predefined patterns of the vehicle class. Appearance-based methods include pattern classification system between vehicle and non vehicle. There are a many works [16][17][18] tackling realtime on-road vehicle detection problem. All the papers used monocular cameras and have real-time constraints. [16] used horizontal and vertical edges (Knowledge-based methods) in HG step. The selected regions at HG step are matched with predefined template in HV step. [17] used horizontal and vertical edges in HG step. However, they use Haar Wavelet Transform and SVMs (Appearance-based methods) in HV step. [18] detected long-distance stationary obstacles including vehicles. They used an efficient optical flow algorithm [19] in HG step. They used Sum of squared differences (SSD) with a threshold value to verify their hypothesis.

This paper describes a modified approach Association [1] [21] for vehicle detection. At each time, the decision of the presence of vehicles in the road scene is made based on the current frame and its preceding one. This method exploits the displacement of edges in the frames. At each edge point in one frame we look for its associate one in the preceding frame. The obstacles can be detected on the basis of the analysis of association results. Adaboost classifier is used to verify is an obstacle is a vehicle.

2. ASSOCIATION APPROACH

This section describes the main steps of the proposed method. We extract the edge points and corners of the consecutive images. We keep only the edge points belonging to curves containing corners. The association is performed between consecutive images. We calculate the association and analyze the results to detect obstacles. Finally, the Adaboost classifier is used to decide if a detected object is a vehicle or not.

2.1 Detecting Corner and Edge

In this subsection We use Shi and Tomasi [20] corner detector and Canny operator to find our points corner and edges and we keep only the edges crossing at least one of the points corners to eliminate others objects such as road and trees for that we augment the performance of our approach.

2.2 Association constraint

2.2.1 Uniqueness constraint

Each feature can at most be associated to one feature in the previous image. That's mean; one feature in the current image should be not associated to more than one in the precedent image. Our algorithm is based a lot on this constraint.

2.2.2 Association continuity constraint

We consider that the physical surfaces are locally continuous, and this continuity is appeared on both current and next frame. In this work, this constraint is satisfied by using the method of Winner-takes-all (WTA) on each edge. Consequently, a connected edge points in the current image must associate to the connected ones in the previous image, which it shares the greatest associated points, then many false associated points are corrected. Another advantage of this constraint is to reduce computation time of pre-estimated map computation step. The associated points should belong to the same object contour and they should have similar or closer gradient magnitudes and orientation. In this work, we use an important cost function (Equation 1.) described below in this paper. This function computes the distance between two candidate associate points using gradient magnitudes. The edge with smaller cost will be considered as associated pairs of features. Because of vertical movement of scene, the association approach does not guarantee that each feature in the image have its associated point. But some good associates' points are enough to construct the vehicle objects.

$$F(d_x) = \min \sum_{x=u-w}^{u+w} \left(I(x,y) - I(x+d_x, y) \right) \quad (1)$$

w: window

d_x: distance between two contours is how many pixel moves the contour of the instant t_0 to time t_1. Given point (u, v) in image t_0 the algorithm finds the point (u + d_x, v) in image I_{t+1} that minimizes function of cost F. see Fig.1.[22].

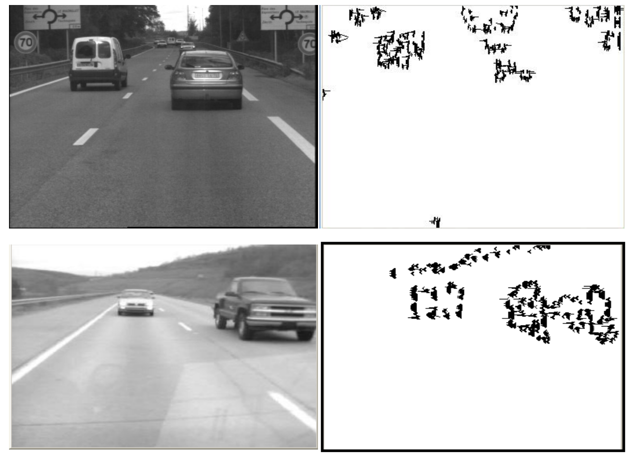

Fig 1: Left: Initial Image. Right: Image Association.

2.2.3 Calculates the true association

The idea behind this step is to eliminate some basic false association due to calculate the normal vector of association in previous subsection [1] [23]. This will make the work of the detection and validation of vehicle easier and less time-consuming. For this sake, we evaluate the temporal matching of each edge as described in Fig.2.

Here, we show how to find the true correspondence between the curves of edge consecutive frames f_{k-1} and f_k based on the association computed in the previous subsection. This involves matching between curves of the image I_{k-1} with edge curves of the image I_k. The Temporal correspondence consists of finding for each edge curve C^i_{k-1} in the set S_{k-1} its corresponding edge curve C^i_k in the set S_k, if it exists. Let Associate (C^i_{k-1}) = $\{Q_n\}_{n=1,\dots,Ni}$ be the set of edge points Q_n, belonging to the image I_k, which represent the associates of the edge points of the edge curve C^i_{k-1}. N_i is the number of associations found for the edge curve C^i_{k-1}. If M_i represents the number of edge points in C^i_{k-1}, $N_i \leq M_i$ because there are edge points in image I_{k-1} for which there is no associate in image I_k. If there is no error in the association process, all the edge points belonging to the set Associate (C^i_{k-1}) should belong to one edge curve, which is the corresponding curve to C^i_{k-1} but there are errors found during the process of association. Consequently, the edge points Q_n may belong to different curves in S_k. We find the match of C^i_{k-1} by looking for the curve C^j_k, which contains the maximum number of edge points in Associate (C^i_{k-1}). We apply the same method to all the edge curves in S_{k-1} to find their corresponding ones in S_k.

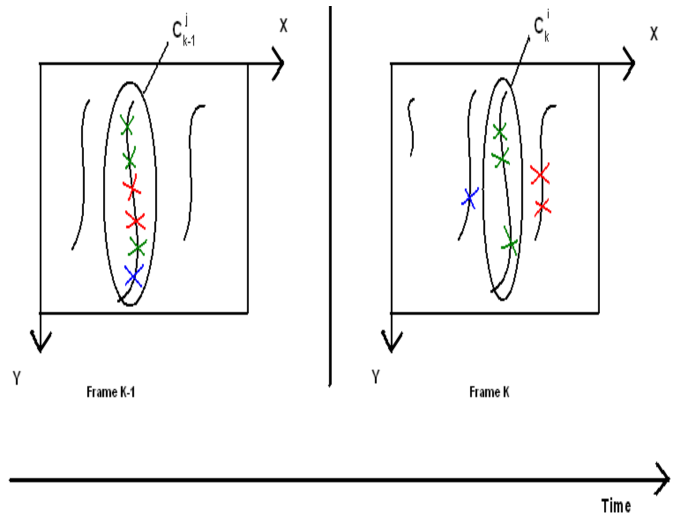

Fig 2 : Correction process for the association

2.3 Detection of Objects and Validation

Here we use our method describe in [1] to find the obstacles and objects from image association computed in subsection 2.2.3. Fig.3.

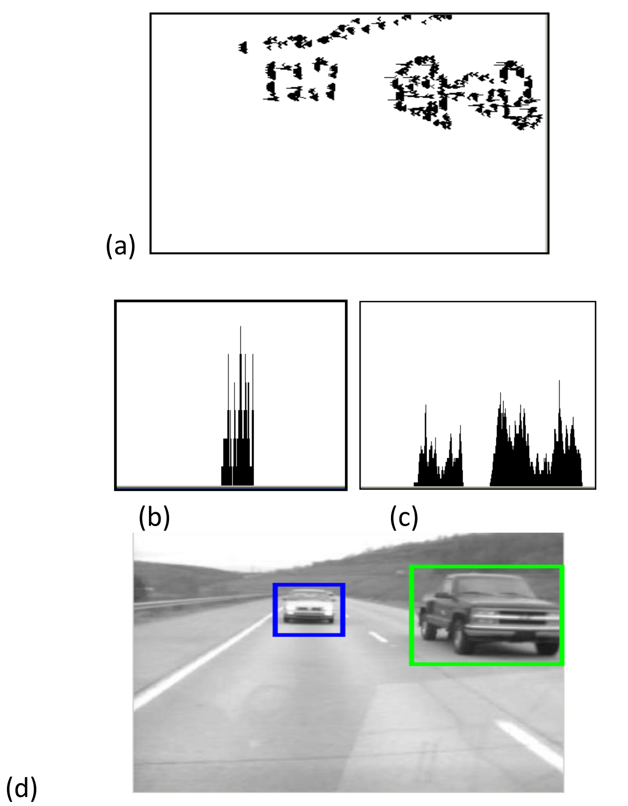

Fig 3: (a) Image Association (b) and (c) the computed function by our method. (d) Bounding box.

3. RESULTS

We have implemented a number of experiments and comparisons to demonstrate the modified Association approach in the context of vehicle detection to demonstrate the performance of our algorithm. The temporal matching of edge curves of consecutive images increases the performance of our approach by corrections of errors found during the calculation of the association.

We tested the system on different frames of images. The system is able to detect most vehicles in different images and give us good and performance results. Fig.4.

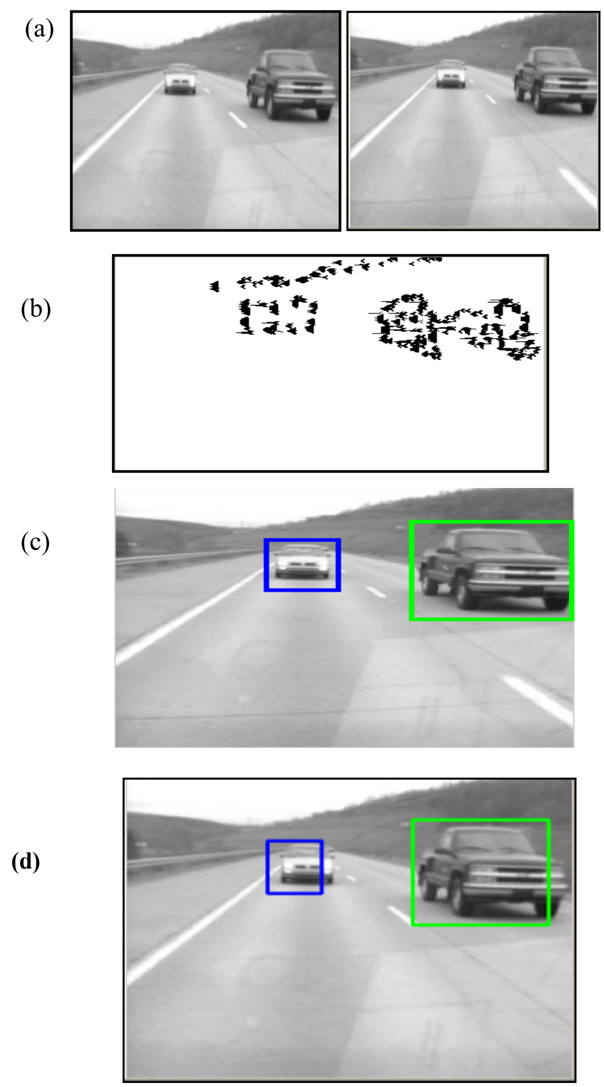

Fig 4: (a) Image at instant t_0 and t_1. (b) Association vectors calculated between instants t_0 and t_1. (c) Vehicle detection after correction. (d) Vehicle detection before correction.

Figure 4 shows a comparison of the results found in [1] and the one of our approach included the Correction process for the association. The results illustrate several Strong points of the proposed method. Figure 4(a) shows an image at instant t_0 and t_1. In Figure 4(b), shows associations vectors for each edge between the frame t_0 and t_1. In Figure 4(c) shows Vehicle detection after the process of correction and finally the Figure 4(d) shows the vehicle detection before correction..

The proposed method has been tested on other real road images depicted in figure 5. The HG and HV results are shown in figure 5.b and figure 5.c respectively. It's clear that the results computed by our approach are very satisfactory.

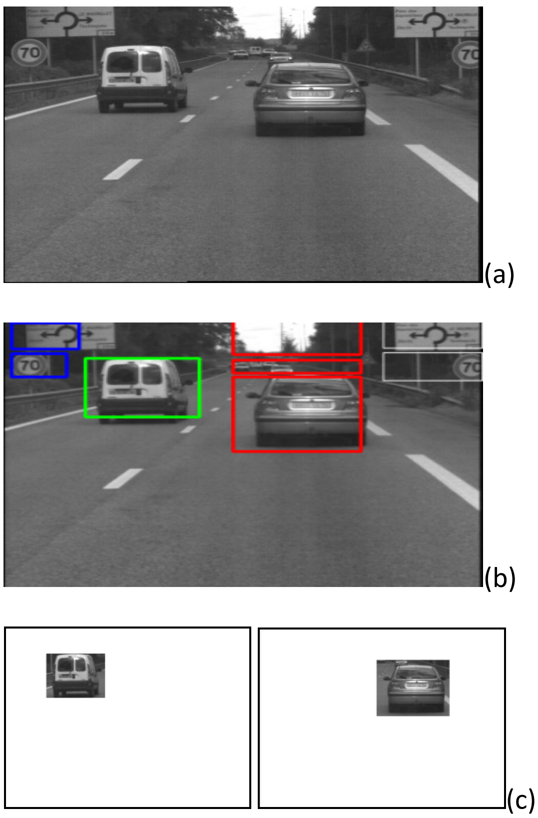

Fig 5 : (a) Original image.(b) Hypothesis Generation (HG) and (c) Hypothesis Verification (HV)

4. CONCLUSION

We have presented a performance method of vehicle detection based on notion association adding other treatment for the calculation of association is the Temporal matching of edge curves of consecutive images including the correction of association describing in the subsection 2.2.3. It can be detect most of vehicle in different images and increases the performance of our approach. Experimental results show that this system is capable of detecting vehicles; it works in real-time conditions and can achieve a high reliability target detection of vehicle.

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