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Vehicle Detection Using Horizon and Base Approaches for the Real Time System

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Abstract. *Vehicle detection is an important problem with application to driver assistance systems and autonomous, self-guided vehicles. The goal was to detect, as much as possible, in real time system the vehicles on images extra road scenes urban, resulting from a base of abundant data. These images are in levels of gray which eliminates the methods using spaces of color. In this paper we will describe the classical methods: horizontal gradients and contour detection used to detect the positions of vehicles in an image. From this study, our work of development is to create, test and improve one of the detecting methods which is the method of horizontal gradient. In this context, we have developed two approaches of horizon and basic and we have showed that the execution time decreases and the detection percentage increases.*

keywords. *Intelligent vehicles, Vehicle detection, Gradient method, Contour detection, Horizon approach, Base approach, Real-time system.*

1. Introduction

The increase in the car fleet is accompanied by an increasing demand of systems that assist to be controlled, promising a protected and comfortable one. Accordingly various researches were undertaken by the community. This results in the installation of the devices of high technologies and other control devices in the vehicles as well as the road. We can classify these systems in various categories of which Advanced Vehicle Highway Systems (AVHS) [1]-[2], Advanced Safety Vehicle (ASV) [3] and Advanced Driver Assistance Systems (ADAS) [4]. Their ability to detect nonco-operative obstacles and to measure the degree of danger is essential for the system of assistance with control [10], [11] Vis-a-vis the critical situation; the system will be with measurement to inform the driver or to take the control of the vehicle temporarily. It is also possible

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to take partial control of the vehicle at the time of monotonous tasks in order to increase the comfort of the driver.

The intelligent visual systems are requested more and more in applications to industrial and deprived calling: biometrics, ordering of robots [20], substitution of a handicap, plays virtual, etc. They make use of the last scientific projections in vision by computer [21], artificial training [22], pattern recognition [23], and fusion of information [24].

Various vehicle detection approaches have been reported in the computer vision literature. [12], [13] which used stereo-vision-based methods (e.g., inverse perspective mapping) to detect vehicles and obstacles. [14], PCA was used for feature extraction and neural networks for detection. [15] called Local Orientation is a method used to extract edge information and neural networks for vehicle detection. [16] used motion and edge information to hypothesize the vehicle locations and template-matching for detection. [17], the statistics of both object appearance and ”non-object” appearance were represented using the product of two histograms with each histogram representing the joint statistics of a subset of wavelet coefficients and their position on the object. [18] proposed a general object detection scheme using wavelets and SVMs.

In our work, we study the processes allowing to detect, as well as possible, in real time system the vehicles on images extra road scenes urban, resulting from a base of abundant data. The database provided contains in addition to the images of the most different road situations possible. Moreover images are in levels of gray which eliminates the methods using spaces of color RGB, HSV or others.

The developed method is inspired of the algorithm of Matthews [6]. This method uses knowledge a priori appearance of the back sight of a car containing of very marked horizontal contours. The first stage thus consists in extracting horizontal contours from the image. In the second time, we have calculated the profile of the horizontal variations by making the sum for each column the horizontal gradients. The presence of a peak in the curve obtained makes it possible to indicate the horizontal position of the corresponding vehicle.

In this paper, we have compared the classical method (horizontal gradients and detection of contours) and the two approaches (horizon and base). The objective is to eliminate two parts of the image, the top and the bottom respectively which contain almost no useful information. This technique allows reducing the execution time while preserving a good detection.

The rest of the paper is organized as follows: In sections 2 and 3, we give the description of the classical method of horizontal gradients and the method of detection of contours. Our approach (Horizon and Bases) and the experimental results will be compared and presented in Section 4. Section 5 contains our conclusions.

2. Method of the horizontal gradients

The horizontal gradient was calculated by taking differences in the image values between columns. Note that the column before and the column after k was used. Use of an odd number of pixels in a gradient calculation prevents a shift in location.

$$B(j,k) = A(j,k+1) - A(j,k-1) \quad (1)$$

If A has gray values in the range 0 to 255, for example, then B may have values in the range -255 to 255. The values of B were renormalized to the range 0 to 255 by shifting and scaling. This can be done by the replacement

$$\left[\frac{B(j,k) - B_{\min}}{B_{\max} - B_{\min}} * 255\right] \rightarrow B(j,k) \quad (2)$$

Where the brackets [.] indicate rounding to the nearest integer.

The developed method is inspired of the algorithm of Matthews which is described in the article [6]. This method uses the knowledge of the priori appearance of the back sight of a car containing of very marked horizontal contours. The first stage thus consists of extracting horizontal contours from the image. In the second stage, we calculate the profile of the horizontal variations by making the sum for each column of the horizontal gradients. The presence of a peak in the curve obtained makes it possible to indicate the horizontal position of the corresponding vehicle.

2.1. Extraction of horizontal contours

The calculation of the horizontal gradients for an image is achieved by withdrawing from the original image its shifted copy of a line. We transform into binary the result and we preserve in white only the pixels higher than a relatively weak threshold in order to eliminate part of the noise while preserving a maximum of information. We proceed then, to filter the preceding image by preserving now only the pixels belonging to a sufficiently long horizontal segment. We have started by planning to limit the length of the segments according to their height in the image then we have decided to fix this threshold at 11 pixels [7]. It is starting from this image that the profile of the horizontal variations is calculated.

Fig.1. The initial image.

Fig. 2. Subtraction between the image and its copy shifted of a line downwards.

Fig. 3. The kept segments have a length greater than 11 pixels.

Fig.4. Detection of three vehicles having different distances.

The profile of the horizontal variations is obtained by making the sum of each column of the image previously calculated in a vector. By observing this curve, we note that it is possible to find the columns containing a maximum of horizontal variations. And as these horizontal variations translate the presence of vehicles obstacles, we can go back to the horizontal position of each vehicle.

2.2. Conclusion

The profile of the horizontal variations is obtained by making the sum each column of the image previously calculated in a vector. Based on this curve, we note that it is possible to characterize a vehicle.

By observing the profiles of the vertical gradients, we note that it happens regularly that a peak characterizing a vehicle presents several maximum buildings (multi_detection). We identify several cases of image at the origin of this problem: reflections due to the sun, the presence of panels or bridges in the zone of the detected vehicle. To solve this problem, at first, we have to emit the assumption more strongly to smooth the curve of the profile of the vertical gradients. However, as this modification would also cause to decrease the rate of detection of the distant vehicles or vehicles whose vertical gradients are weak. We thus decided to preserve this smoothing at the detriment of multiple detections of the same vehicle.

The number of omissions inevitably increases if we increase the threshold. If the omission of relatively far vehicles is not too serious, the detection of the close vehicles is not rather problematic. They concluded at the observation that the close vehicles which are not detected are generally dark color. Indeed, we have observed that horizontal contours which characterize the vehicles are fewer for the dark vehicles.

3. Detection of contours

Contours constitute essential information for certain applications of image processing. In particular, contours of an object in general make it possible to characterize its form. The detection of contours can be realized due to filters or (masks) whose coefficients were carefully selected [8]. It is said that there is a contour when one detects a material change in the intensity in the one of the directions (axes of X and axes of there).

3.1. Choice of the filter

Many filters are used in the image processing field. In our application, we tested this following:

a- Mask of Prewitt: This filtering combines a derivative and a filtering. It creates an image where edges (sharp changes in grey level values) are shown. Only a 3x3 filter size can be used with this filter.

This filter uses two 3x3 templates to calculate the Prewitt gradient value as shown below:

$$\text{Horizontal filter:} \quad Y = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{pmatrix} \text{; Vertical filter:} \quad X = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \tag{3}$$

Apply the templates *X* and *Y* to a 3x3 filter window (*K*):

$$\text{Filter window:} \quad K = \begin{pmatrix} a1 & a2 & a3 \\ a4 & a5 & a6 \\ a7 & a8 & a9 \end{pmatrix} \tag{4}$$

Where $a1$, $a2$, ..., $a9$ are grey levels of each pixel in the filter window.
We obtain finally:

$$\begin{gathered} X = -1*a1 + 1*a3 - 1*a4 + 1*a6 - 1*a7 + 1*a9 \\ Y = 1*a1 + 1*a2 + 1*a3 - 1*a7 - 1*a8 - 1*a9 \\ \text{Prewitt Gradient} = \text{sqrt}(X*X + Y*Y) \end{gathered} \tag{5}$$

b- Mask of Sobel: This filter combines a derivative and a preliminary filtering of the mask of Prewitt. It is largely used in the image processing as a result to its weak error. It creates an image where edges (sharp changes in grey level values) are shown. Only a 3x3 filter size can be used with this filter.

This filter uses two 3x3 templates to calculate the Sobel gradient value as shown below:

$$\text{Horizontal filter:} \quad ; \quad Y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix} \quad \text{Vertical filter:} \quad X = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \qquad \textbf{(6)}$$

Apply the templates *X* and *Y* to a 3x3 filter window (*K*) given in equation 4:

We obtain finally:

$$X = -1*a1 + 1*a3 - 2*a4 + 2*a6 - 1*a7 + 1*a9$$
$$Y = 1*a1 + 2*a2 + 1*a3 - 1*a7 - 2*a8 - 1*a9 \qquad \textbf{(7)}$$
$$\text{Sobel Gradient} = \text{sqrt}(X*X + Y*Y)$$

c- Mask drift of Gaussian: Visually the filters of Prewitt and Sobel give similar results. The filter Robert gives very thin contours (that is with the low dimension of the filter) but noisier. When the threshold is decreased, contours are broken, so there will be to more noise (false contours). When the threshold is increased, one has less of noise, but certain contours are not detected any more. There is thus a compromise to find. The existing methods determine the threshold automatically, according to a certain criterion. The coefficients applied to the threshold correspond to the relationship between the sums of the absolute values of the coefficients of the filters. Indeed, for a contour of amplitude given, the answer of the filter is proportional to this sum. So the threshold must be corrected consequently. For example, for Prewitt this sum is worth 6, and for Robert, it is worth 2 for a contour of amplitude given, the answer of the filter of Prewitt will be thus three stronger than the answer of the filter of Roberts, one the multiple thus threshold applied to the filter of Roberts by 1/3 to compress.

3.2. Detection of horizontal contours

Following these comparisons, we found that the filter of Sobel made a compromise between the performance and the speed, but the filter of Robert is faster. We will establish our filter at the end of this study in accordance with the obtained results in term of performance of detection and the execution time.

We can make the detection of horizontal contours directly to the assistance of the specific filters as shown in figure 5. But the result obtained is not powerful though time runs faster compared to the method of the subtraction (figure 6).

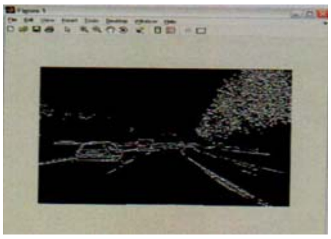

Fig. 5. Horizontal contours by specific filter.

Fig. 6. Horizontal contours after subtraction between the image and its copy shifted of a line downwards.

4. New Approach for the Real Time System

The objective is to eliminate two parts of the image, the top and the bottom respectively which contain almost no useful information. This will enable the possibility of decreasing the execution time and make it possible and good in detection.
For the real system, we propose to use two approaches: Horizon and Base approach.

4.1. Our approach-horizon

Our principle following a good result in detection is to minimize the execution time the least possible to be able to carry out a treatment in real-time.
After having minimized the size of the image, we seek to eliminate the zones from the image which do not contain almost any necessary information in detection.

4.1.1 Principle

The horizon is characterized by the values of the pixels which we have considered their value threshold of Index is equal to 200.
It was noticed that the Horizon almost does not contain useful information's in our case if the very whole line were in the zone of the Horizon. Then, one can firstly eliminate the lines which are entirely in the zone of the Horizon.
Let us take the following figure:

Fig. 7. The red line is in the horizon part of the image with ratio equal to 100%.

It is noticed then that under the part which is to 100% in the Horizon one can have pixels under the given threshold but which do not contain useful informations, of where the possibility of decreasing this percentage of necessary Horizon pixels.
Our studies showed that the threshold of the percentage can be fixed at 60%, i.e. we cut out from the image the part in which one has 60% of the line is in the Horizon.
Let us note that:

1- Minimal size of the vehicle to detect (i.e. until with which distance one must always detect the vehicle), the impurity of the Horizon, as of another criteria form the base of our choice.

2- The sweeping of the image is not stopped when one finds a line which unless 60% as of its pixels except Horizon one must treat then until to 80% of the image because in some case: bridge, posts,… if one stops before arriving at the greatest value of there where the Horizon pixels form more than 60% of the pixels one is likely to keep useless parts in the image. Then one can never find a line with 60% of Horizon pixels to the lower part of the road.

Fig. 8. Horizontal line stops to y=20.

Fig. 9. Horizontal line stops to y=0.

So in the image of the figure 8 (respectively figure 9) one wanted to less stop sweeping with the first meeting of a line having than 60% of pixels Horizon one has to stop us with the line y=20 (respectively y=0).

We can stop sweeping with ~50% of the image but suppose some change on the level of the road (though it is not the case of our study: motorway) then we considered that at worst the case we can treat a rise of the camera until to 80%.

To be able to find the new percentage we have to take an image which presents the worst case.
The execution of our algorithm gives the following result: Limit of the Horizon east for U=242 (to up Y=242).

Fig. 10. The red line is in the horizon part of the image with ratio equal to 60%.

It is noticed that the horizon east to the top of the vehicles, then the fact of excluding the Horizon part of the image does not affect the useful informations for detection.

4.1.2. Conclusion

It is noticed that this method decreases the execution time until 2.27 seconds.
The reduction is relating to the image.

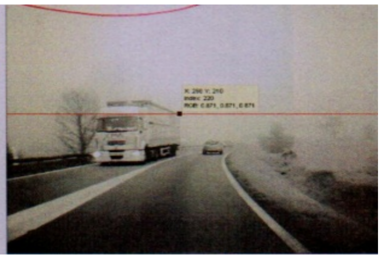

Fig. 11. Limit of horizon at Y=216. **Fig. 12.** Limit of horizon at Y=220.

It is noticed that in Fig 12, the horizon east to the lower part of the limit of the truck but that does not affect detection the last one.

Only large vehicles can get along for a distance, at least large to the top of the road (that depends on the distance which separates us from the vehicle), and because of the big size of these vehicles one finds that they contain much line, then the horizontal effect to exclude part of the vehicle in the treatment does not affect his detection.

Fig. 13. Detection of two vehicles with different sizes.

4.2. Our approach-base

Our second approach to reduce the execution time is the Approach - Base. We always seek to eliminate the zones from the image (road) which does not contain almost any necessary information in detection, but this time the base of the image is treated.

It is noticed that the lower part of the image almost does not contain useful informations, and then one will try to detect this useless part.
By sweeping the bottom of the road to the top one distinguishes what exists from a vehicle by detecting the shade of this vehicle, which is made of pixels whose value of indexes is < 26. Size minimal of pixels shade to detect (i.e. until which distance one must always detect the vehicle), the impurity of the Horizon, as of another criteria form the base of our choice.
Our studies showed a threshold of 7%, i.e. one stops the sweeping of bottom towards top when one detects a segment of pixels shade length more than 7% of the width of the image.
Our principle following a good output in detection is to minimize the execution time at least possible to be able. Then, one can firstly eliminate the lines which are entirely in the zone of the Base.

4.3. Results

In this paragraph, to prove the good performance of our two approaches especially in real time system, some statistics were made on a database sample (69 images). We apply for that, three different programs:

1- SUD: (i.e. without UP DOWN). We directly treat the image without applying the methods of our Approach-Horizon and our Approach-Base. We have to apply this program in both cases of filter Sobel and Robert, but it is noticed that though time execution is decreased, the output of the treatment decreased thus in a very clear way then one dropped the filter from Robert, and we have continued this program and the two programs which follow without applying the filter of Robert i.e. with Sobel alone.

2- U: (i.e. with UP). We directly treated the image without passing by the phase of compression, but there is bracket the method of our Approach-Horizon.

<u>3- UD</u>: (i.e. with UP DOWN). We apply the method of our Approach-Horizon combined with the method of our Approach-Base.

In our study, we focus our comparison on the two following principal parameters:
–Percentage of detection.
–Time execution.

Table 1. Percentage of detection and time execution for the three procedures.

	SUD	U	UD
Number of detection	62	61	60
Percentage of detection	89.85%	88.4%	86.95%
Time execution average	3.5 sec	2.7 sec	2.9 sec

It is found that the most rate of detection is that of program SUD, and it is normal because the image is taken such as it is without any modification or partition (Horizon - Base). But the execution time cannot at all be regarded as real-time even if one takes into account material environment used. We can improve the result with a material more sophisticated but one always seeks to minimize the execution time at least possible.

It is found that the fact of applying the method of the horizon (U) decreased the execution time in a remarkable way while keeping the output of detection very close to that of program SUD (with one 1.45% of difference).

Then one can deduce that the method our Approach-Horizon has given a good performance.

Following the fact of applying the method of the horizon (UD), we apply in more the method of the base. It is found unfortunately that time execution increased whereas the goal of this method is to decrease the execution time.

But in some case such that figure 14, we prove that the method "Base" helped in the reduction in the execution time (see table 2).

Fig. 14. Detection of 5 vehicles among the six ones presented in the image.

Table 2. Number of detections and time execution for the image of the figure 14.

	U	UD
Number of detections	5	5
Total number of vehicles	6	6
Time execution average	2.27 sec	2.3 sec

5. Conclusion

In this paper, we have presented a classical system allowing the detection of vehicles by the horizontal gradient method. In this process, we extract horizontal contours from the image, and then we calculate the profile of the horizontal variations by making the sum for each column of the horizontal gradients. The presence of the peak in the curve obtained will indicate the position of the vehicle.

In order to minimize the time of execution to the least possible so that it can carry out a treatment in real-time, we have proposed a method presenting Horizon and Bases Approaches. The main idea is to eliminate the zones, from the image (road), which do not contain any necessary information for detection. This is why we have obtained an acceptable detection with a minimum time execution.

For our process, a statistics were made on a sample of the database. The best result obtained is with the program “U” (with UP) with a rate of detection of 88,4% and the average execution time/image 2.27 seconds.

In spite of this result, the two approaches “U (with UP) and UD (with UP DOWN)” are still equally necessary and important for other database.

This result can be improved even more by decreasing time, by using a more sophisticated hardware and a clearer image to profit from our approach which already proved its good performance.

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