VEHICLES RECOGNITION BY VIDEO CAMERA

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Abstract. The paper presents the recognition of vehicles considered as obstacles in the road, in order to avoid collision. An inboard video camera is used as an optical sensor to supply exterior scene information. The algorithm of vehicle detection from video image, built by morphological transformations (Serra 1982), is proposed. The advantage of the proposed approach is the reliable recognition for various models and colors of vehicle, and the good efficiency for difficult case like distant vehicles and lateral sun shadows. The experimentation has been done on a large amount of data. Some of results is given in the article.

Key Words: traffic control, vehicle, obstacle avoiding, sensor, image processing

1. INTRODUCTION

This paper describes the algorithms for vehicles detection as obstacles in a road. The research has been done at the Center of Mathematical Morphology -(C.M.M.) in France, in the framework of the PROMETHEUS European project (Beucher 1990, Yu 1992, Yu 1993). Under the supervision of French automobile industries RENAULT, PEUGEOT and CITROEN, the project aims at improving driving security by means of a perception system based on computer vision. Vehicles are the most frequent obstacles in a road for daily driving. Their recognition should depend on their relative position with respect to the optical sensor. The paper deals with the case of the view ahead or behind for vehicles in a highway or country road. Two kinds of inboard sensors can be used to receive the vehicle information: telemeters and video cameras. The use of video camera allows the road edges tracking and the obstacles recognition to be coupled by only one sensor.

The existing algorithms for vehicles recognition in a video image can be classified into two main groups: The first group is based on optical flow field. It exploits the information of the vehicle's motion by calculating velocity field from the optical observation. The apparent size of the vehicle should be quite large for reliable recognition. Furthermore, the motion of the camera, i.e. the velocity of the vehicle, should not be significant, otherwise, the other objects in the scene will cause false detection due to their relative motion with respect to the camera. The rejection of the false detection is very difficult, due to the poor precision of object's shape archived by the approach. The second group consists in contour analysis of the candidate regions. The shape of a vehicle can be represented by some geometrical characteristics, like coins, segments, and closed regions, etc. These criteria are valuable only if the apparent size of the vehicle is large. For small vehicles, these geometrical characteristics will be confused with noise and become no significant. Moreover, both of the approaches are based on the observation of the vehicle's shell, and depend thus on their grey tones. For those who have a grey tone almost equal to that of the road, the mentioned approaches will fail because of the lack of contrast between the object to detect and the background. To overcome the above difficulties, a new approach is proposed in this paper. It is independent of vehicle's model and color, and efficient for a large range of distance. The recognition process can be described by the detection of candidates and the application of some criteria to reject the false ones. The details of algorithm are given in the following sections.

2. CANDIDATE DETECTION

As the vehicle's shell may have poor contrast with respect to the road background, other parts of the vehicle should be studied. In fact, the low part of the front or back represents a good marker for any models of vehicles. The examination of numerous video images has shown that these parts are always darker than the road background (see figure 1). This is true for all weather conditions, traffic situations, and vehicle types. The dependence on vehicle color is then avoided. The observation done above remains valuable for distant vehicles having very small apparent size.

The detection of candidates can be realized by searching for the regions darker than the road. Dark regions

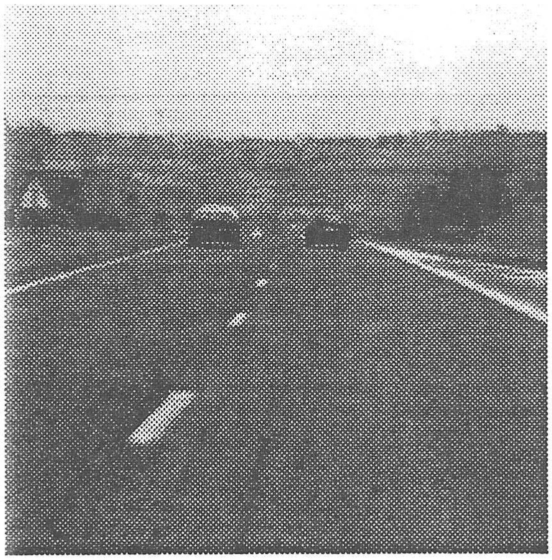


Figure 1: An initial image of vehicles

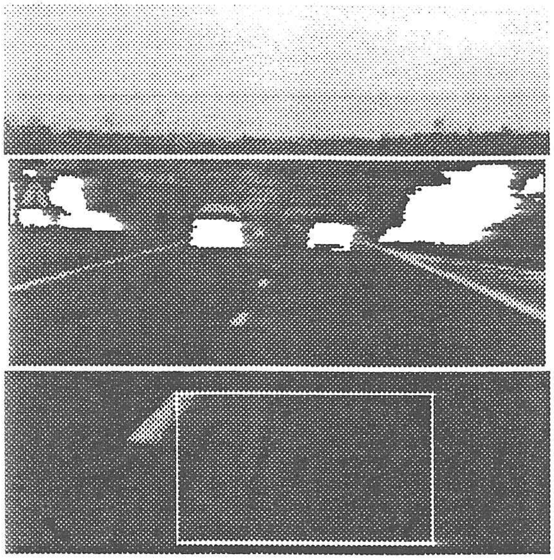


Figure 3: Binary dark regions detected by numerical reconstruction

are detected by a morphological transformation called *numerical reconstruction*. The relation of grey tone between different objects in a typical road scene is illustrated in the figure 2a. For easier comprehension, the signal is inversed in the figure 2b, where the white regions should be considered as vehicles. The numerical reconstruction to extract a white regions is expressed as follows. Firstly, the initial signal f is subtracted by a constant h, giving a signal $f-h$ in the figure 2b. The numerical reconstruction g of signal $f-h$ in the mask f is the iterative morphology dilations (Serra 1982) of $f-h$ in the mask f until idempotent (figure 2c).

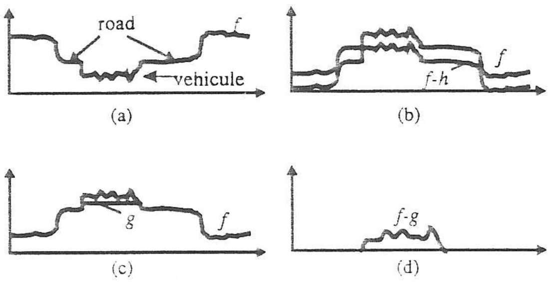


Figure 2: Numerical morphology reconstruction

The residue (figure 2d) of the reconstruction $f-g$ represents the detected white regions, or dark regions in initial image. In this transformation, the parameter h has to be determined. It characterizes the dynamic of luminance variation, and is determined by an adaptive manner. A constant value of the parameter can not satisfy the unpredictable luminance variation of the road scene. In fact, for each image the value of h can be deduced easily from histogram information, which should be calculated in a window including road pixels. Such a window is shown in the figure 3 by a rectangle placed at the bottom of the image.

The variance σ of this histogram can then be considered as that of the road luminance, because almost all pixels used to calculate the histogram belong to the road surface. The value of h is then deduced from σ. Sometimes the small window in the bottom of the image can include some other pixels than those of road, like lane markers, spots, and trace of vehicle wheels. The presence of these objects causes the variance of the histogram to be different from that of the road luminance. One alternative method to reduce the influence of other objects consists in enlarging the windows, but this will include vehicle objects. Finally, a very simple method is suggested to resolve this conflict: adding histograms in the same windows but at different instants. As the motion of the camera, the small windows represent different road sections in real world. The percentage of the number of no-road pixels with respect to that of the road pixels is reduced, because the number of road pixels is increased due to the addition of some other road sections. The influence of unexpected pixels is thus reduced.

The dark regions got by numerical reconstruction is given in the figure 3. In order to minimize unnecessary operation, the search of dark regions is only done in the window at the middle of image. The shapes of the detected binary regions in the road (see figure 3) are regular, which are equivalent to that of vehicle. But this is not always the case. Sometimes the dark region attached to a vehicle can be much smaller than it. To get good contour shape of vehicle's front or back, a morphological transformation *watershed* is used. It is a non parameter transformation (Beucher 1982) applied to the gradient module of an initial image, but a marker is necessary to be put into each object. The dark regions detected by numerical reconstruction are used here as the markers for watershed transformation. The figure 4 shows the vehicle contours determined by the watershed transformation. In this special example, there is no evident difference between the contours of watersheds regions and those of numerical reconstruction.

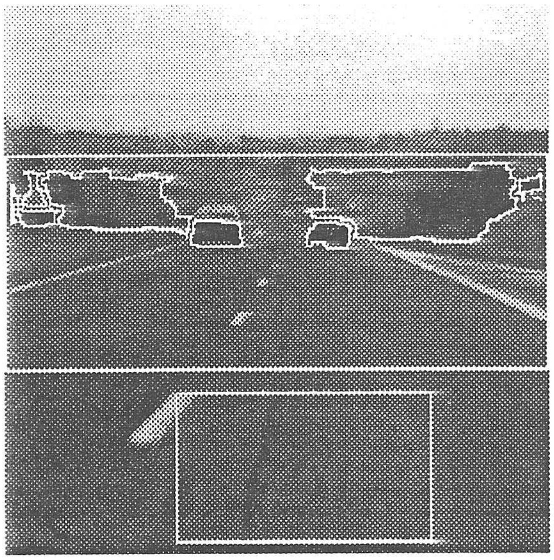


Figure 4: contours of dark regions detected by watersheds

3. CRITERION OF GRADIENT

Among all candidate regions, some of them are not the vehicles, and should be rejected by a certain criterion. In the example of figure 4, there is no false detection in the road, but there could be if some dark spots are present in the road. Several false detections are produced outside the road. In fact, those false detections outside the road can be easily eliminated by considering only the candidates inside the road, if the result of the road edge detection is supported (BEUCHER 1994). To examine the effect of the criterion of rejection on unsignificant irregular objects, the false detections in this example are not eliminated by road edge information.

The first proposed criterion is derived from a geometrical characteristic, i.e., the back or the front of a vehicle is always composed of some horizontal and vertical segments. This geometrical description of vehicle is more universal and pertinent than the description of coins and shapes. The last one can not be valuable for all models of vehicle and becomes unsignificant for distant vehicle. The segment lines description can be formed by the directional gradient criterion. Let g_0 and g_{90} be respectively directional gradient module of the initial image in the direction 0 and 90, and $g = MAX(g_0, g_{90})$ the combination of the gradient in two directions. For each candidate region, the volume of gradient module normalized by the area is calculated. This measurement gives high values for the regions including the horizontal and vertical segments. The false candidates due to the spots have irregular forms, and they are not composed of significant segment lines. They will be then eliminated for their low values of directional gradient volume. The figure 5 gives the result of candidate selection by this criterion, where only the baselines of retained candidates are drawn in the figure. The heights of the vehicles are not indicated because the contrast of the high parts of vehicles depends upon their color and is not always good. Any way, the information of height is not important. The useful parameters for driving security are the distance of the obstacles ahead and behind, and their horizontal extensions (width).

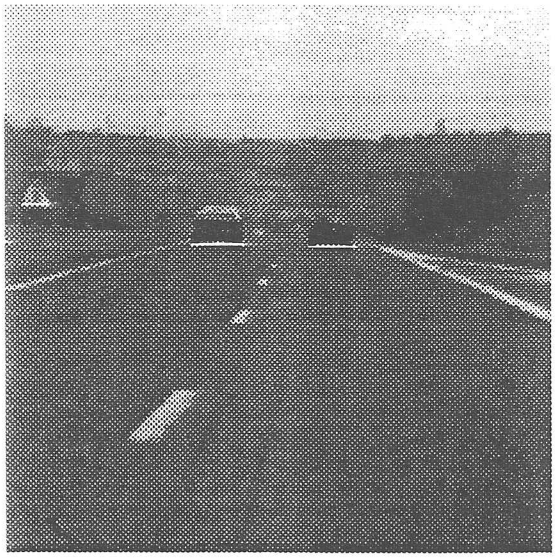


Figure 5: baseline of objects recognized by gradient criterion

As the figure 5 shows, the traffic sign at the left side of the road is also retained by the criterion of gradient volume, because it includes some horizontal and vertical segments. That means that the approach developed in this paper can be used to recognize other manufactured objects, since they are often composed of segment lines.

4. CRITERION OF SYMMETRY

To make the decision of the rejection of false candidates, a parameter should be introduced as the threshold of gradient volume. The value of this threshold should not be determined seriously, in order to avoid rejection of real candidates. On the other hand, this may cause a insufficient rejection, and false candidates will be retained after the application of this criterion. Therefore, another criterion, geometrical symmetry, is introduced here for second rejection. Obviously, all vehicles have a symmetric form. But this criterion should not be exploited simply upon the form of the binary region. Under the influence of noise, the shapes of the front or back of vehicle are sometimes not regular; especially for distant vehicles, the apparent dimension of a vehicle may be only in order of several pixels, and the perturbation of the noise may also be in the same order. The symmetry for far vehicles will then loose any signification.

To avoid this disadvantage, the criterion of symmetry proposed here does not depend directly on the contour shape, but exploits the information of grey tones in the initial image. The figure 6 explains the principle of this criterion. The figure 6a represents an initial image or signal. Let x_0 be an axis of mirror. By reflecting the left side of the signal to the right side of the axis, the two signal are superposed at the right side in the figure 6c. The module of the difference of two signals is given in the figure 6e. The signal in (e) represents the residue of the difference of two superposed signals. The surface $s(x_0)$ of the residue is then calculated in the interval of $[x_0, x_0 + D]$, with D as the half-width of the region in examination. $s(x_0)$ has a small value if the axis x_0 is the same as that of vehicle, and a large value if it is not the case (the figures 6b,d,f).

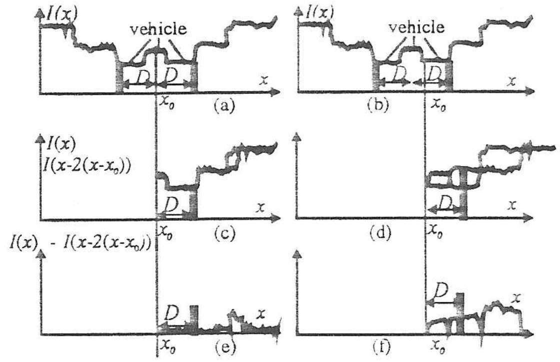


Figure 6: Definition of symmetric value

Considering each line y of initial image as one signal, a family of functions $s_y(x_0)$ is available. Each function for a given y has its form like the figure 7a with some irregularity. To reduce this irregularity, $s_y(x_0)$ is integrated for y in a vertical interval, and normalized by the height of the vertical integration interval, giving $S(x_0)$ as result.

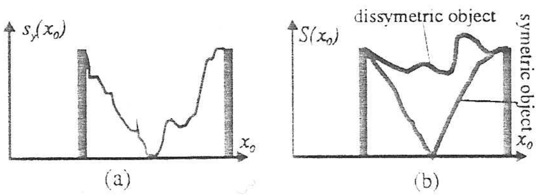


Figure 7: Symmetric function

In the symmetry calculation, the horizontal and vertical interval of integration have to be known, they are justly the width and height of the binary region in examination. The figure 7b shows that the integrated symmetry function $S(x_0)$ has a much more regular form. For symmetric objects, the function has the form of an inverse triangle, and it has an irregular form for dissymmetrical objects. That means that the form of the symmetry function can be used as a criterion of symmetry. But a scalar value should be introduced to describe its form. This value can be calculated from certain characteristic points of the function. For example, it can be the ratio of minimum value and the value at the extreme sides of the function. The minimum point of the function has a significance, it is the median axis of the vehicle. It should be pointed out that median axis of the vehicle are not always the same as that of binary region attached to it. This remark implies a very important utility, which will be demonstrated in the next section.

The figure 8 gives the median axis and baseline of objects retained after symmetry criterion. The traffic sign at the left side of the road is retained, but this will not cause false detection since it is outside the road.

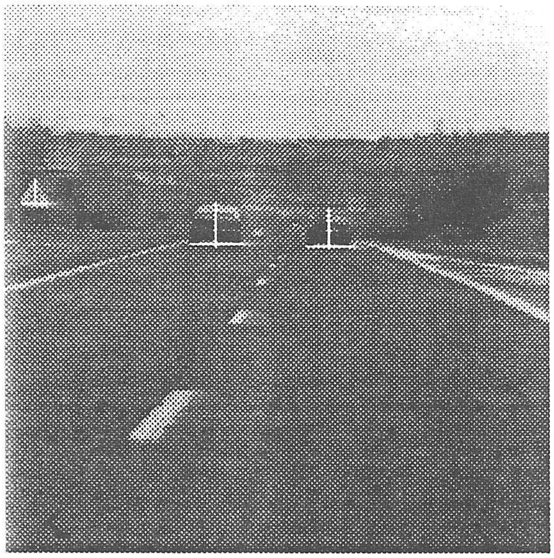
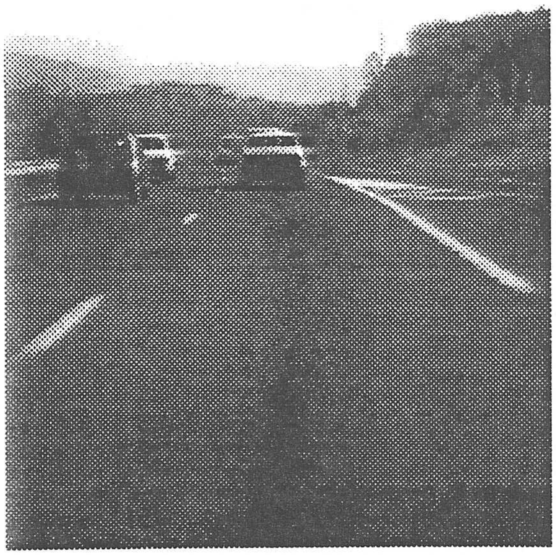


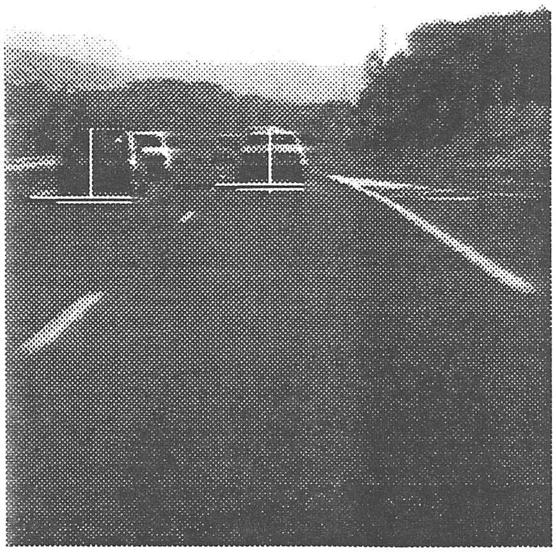
Figure 8: Baseline and median axe of vehicles

5. EXPERIMENTATION

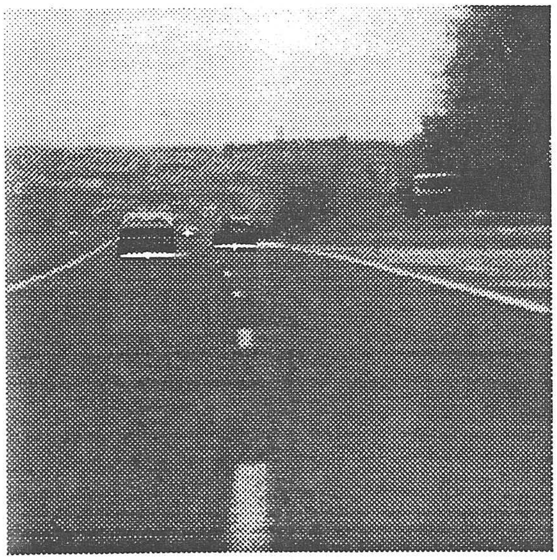
The algorithm has been tested on numerous images. Some typical results are given in the figure 9. The figure 9a represents a very difficult case, where the vehicles produce their shadows in the left side due to sun light from the right side. These shadows are connected to the dark regions of vehicles. After the segmentation by watersheds, the dark regions overflow by the left of the real width of the vehicle. A solution is needed to resolve this problem. The proposed solution in this paper is very simple and efficient. The method uses the information of the median axis of vehicle to correct the overflowed part of width: The two longer horizontal bars in the figure 9b indicate the baseline of detected vehicles. They are longer than the real width of vehicle. The two vertical lines represent the median axe of vehicles, which cut the longer horizontal line in two parts. The median axis is correctly determined in this case, because the symmetry calculation is done in initial image, instead of binary regions. The shorter parts are equals to the half size of the real width, in spite of the presence of lateral shadows. By reflecting the shorter parts to opposite side of the median axe, the complete size of real width can be known correctly (the shorter horizontal baselines). The operation does not need any supplemental calculation, since the median



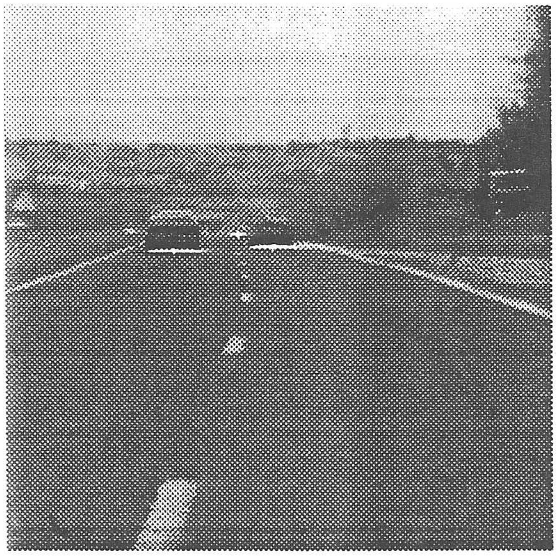
(a)



(b)



(c)



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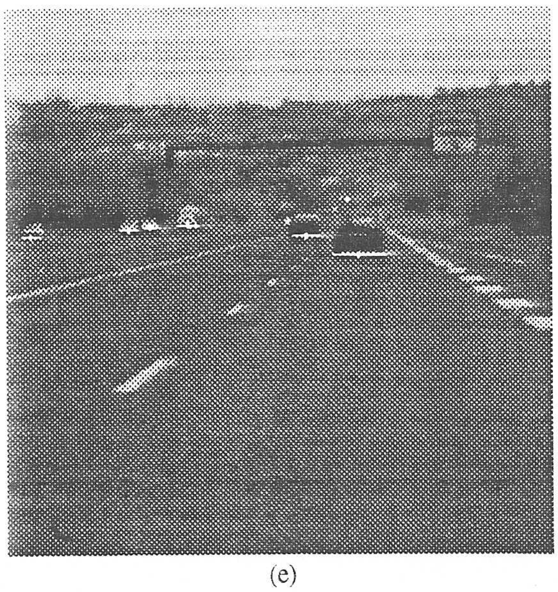
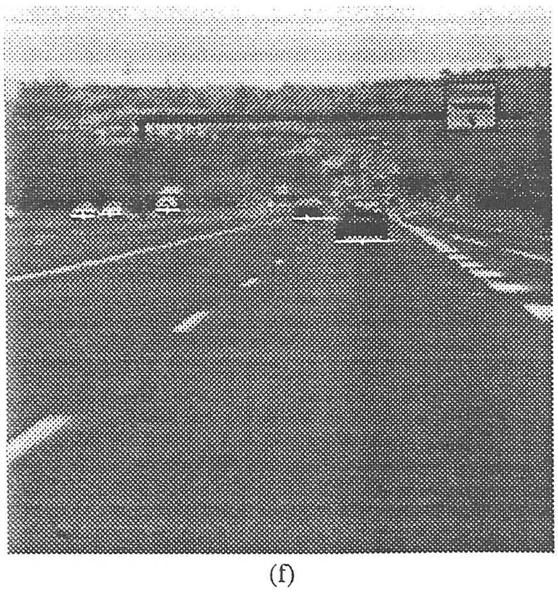


(e)



(f)

Figure 9: Supplementary results

axis information is delivered by symmetry criterion.

As mentioned in the introduction, the approach should have a good performance of recognition for distant vehicles. Some examples of distant vehicles are shown in the figure 9c,d,e,f. From the figure 9c to figure 9d, the vehicle carrying the camera moves from the left lane to the right lane. The vehicle in front of the camera and at normal distance are correctly recognized. A vehicle appeared in the horizon is also recognized. The dimension of this vehicle is equal to several pixels, and all other existing approaches depending contours analysis will fail in this case, because the shape of small vehicles will loose any signification. In the figure 9e,f, the vehicles are recognized in more difficult cases, i.e., the vehicles in the left road have very small apparent size, their base part are partially hidden by a central separation bar. The examples prove that the recognition can give satisfactory results even in these extremely difficult cases.

6. CONCLUSION

The paper proposed an efficient approach to recognize the vehicles as obstacles in a road. The particular advantage of the developed algorithm is that the recognition does not depend on the color or model of vehicle, and has a good efficiency for the extremely difficult cases as vehicles at far distance and the problem of lateral shadows. The algorithm has been tested on a large amount of data representing different weather conditions and traffic situations, giving satisfactory results. The algorithm is now implemented in a specially devoted hardware for real time application, in the framework of the French testbed of intelligent vehicle PROLAB2.

7. REFERENCES

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