Early Obstacle Detection Using Region Segmentation and Model Based Edge Grouping

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Abstract— **This paper describes a system able to detect obstacles as soon as they appear on the horizon by the analysis of a sequence of images recorded by a forward looking TV camera mounted on a vehicle. It exploits several suggestions coming from the a priori knowledge of the scene where the vehicle is moving. The evaluation of the luminance differences between obstacle and road surface and the correlation of motion in succeeding images are the main tools used to formulate obstacle hypotheses. A dynamic model based matching algorithm performs the recognition and the validation of the obstacle.**

I. INTRODUCTION

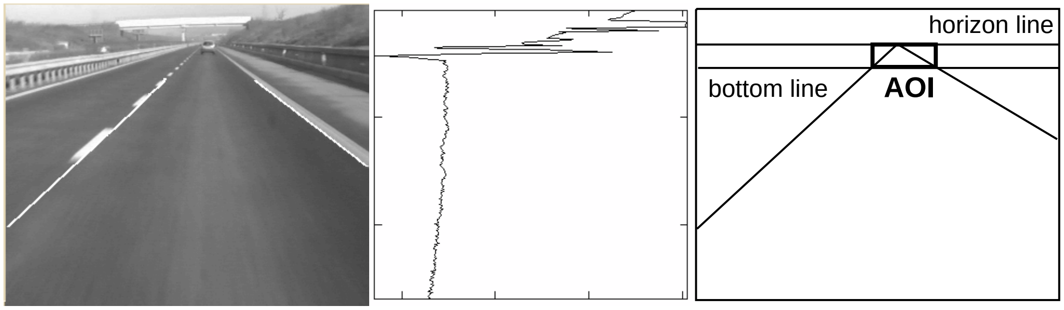
The detection of vehicles (potential obstacles) moving ahead, on the same lane, is essential to keep a safe distance and to provide warnings about dangerous situations. Computer vision systems can support reliably this task, analysing sequences of images recorded by a vehicle-mounted, forward looking, camera.

Several approaches have been so far proposed, however they limit the detection up to about 45 meter, if their vision systems are equipped with usual cameras (2/3" sensor and 12.5 mm lens, which are well suitable to fulfill most of the traffic applications) [1],[2]. Indeed, they need that far away obstacles be analysed at a high resolution to point out those features which are crucial for developing reliable detection and recognition algorithms and moreover far away obstacles are difficult to be detected because they are often merged with background. In order to be effective, obstacle detection must be performed as soon as possible, that is, when obstacles loom on the horizon. Better performances have been obtained using cameras with greater focal length (e.g. 25 mm), which allows the detection and the tracking of obstacles up to a distance of 80 m [3].

This paper faces the problem of formulating distant obstacle hypotheses, using a single camera with normal lenses, and proposes a strategy for the subsequent validation while they approach.

II. THE PROPOSED STRATEGY

The strategy that has been developed draws inspiration from the behavior of the visual system of humans driving vehicles. Firstly, people perceive obstacles mainly because their luminance substantially differs from background, besides they know where to look for and are familiar with the profile of the searched objects, finally they exploit the slow apparent motion of these objects to distinguish them in a cluttered background and perform their tracking in space and time. So a knowledge-based model-driven approach has been investigated, which exploits the persistence of some peculiar structures of the image in the sequence to perform a reliable detection and recognition of the searched objects. Three modules form the system: a lane boundary detection algorithm is used to reduce the search area where possible obstacles can be found, then a far away detection algorithm is devoted to formulate obstacle hypotheses, and finally a validation algorithm checks the correctness of the de-



a **b** **c**

Fig. 1. The area of interest (AOI) definition.

tection by recognizing the obstacle.

III. Lane boundary detection

The lane boundary detection algorithm performs a region growing approach: starting from the region of the image just in front of the vehicle, it extends this region up to the lane marks painted on the road surface. The a priori knowledge of road models allows to overcome difficulties that arise when interrupted lane marks, horizontal road marks, junctions, and exit ramps are present. The algorithm is organized in three phases: the first one detects the boundaries in a first image, while the second tracks these boundaries in the sequence. A boundary consistency check phase completes the process and controls the correctness of the detected borders, starting new searches if incorrect results are detected. The algorithm is fully described in [4].

IV. Obstacle hypothesis formulation

The knowledge of the lane boundaries is used to define a rectangular search area (area of interest AOI) at the end of the road where the obstacles appear. The vanishing point computed using the lowest part of the lane boundaries is used to define the horizon line, which limits the top of the AOI (figure 1a). The bottom line limit is placed in correspondence of the first occurrence (from the bottom) of a negative transition of the function

$$G(r) = \frac{1}{(rb(r) - lb(r))} \sum_{c=lb(r)}^{c=rb(r)} f(r,c)$$

$$\begin{cases} 0 < r < image\_y\_size \\ 0 < c < image\_x\_size \end{cases}$$

which represents the mean pixel luminance on each row of the image between the lane boundaries ($lb(r)$ and $rb(r)$ are the displacements of the left and right borders respectively) (figure 1b). This abrupt and consistent change is due to the shadow always present under vehicles.

If this bottom line is not detected before the end of the lane boundaries no obstacle is present. The lateral limits of the AOI are placed in correspondence of the intersection of the left and right lane boundaries with the bottom AOI line (figure 1c).

Since obstacles are perceived because their luminance differs from the road surface, the luminance of the pixels inside the lane is averaged to predict a luminance reference value which is used to label the AOI points as "road" or "non-road". "Non-road" pixels are processed, firstly, to improve the lane boundary detection and, later, to point out those regions that have a high probability of belonging to obstacles. Finally, region growing algorithms improve this labeling using neighbour similarities. A tracking procedure checks the consistency of these hypotheses, verifying the persistence of these regions in the succeeding images. The bounding box of

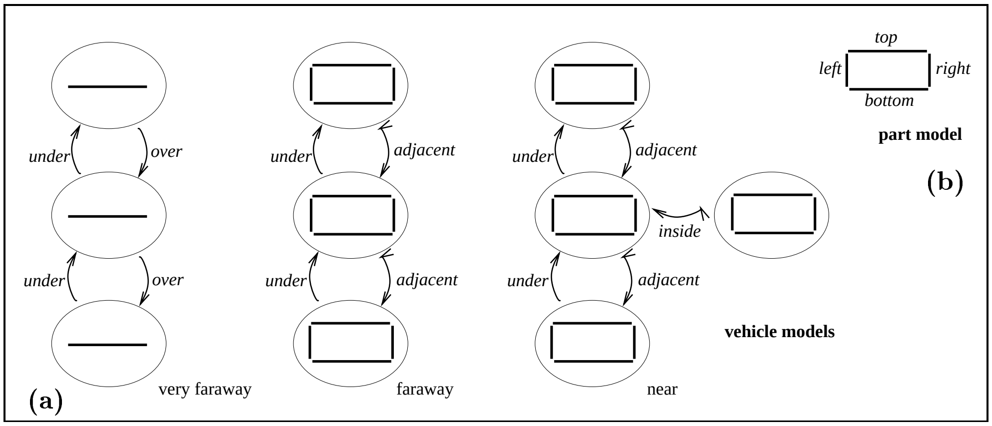


Fig. 2. Dynamic model of a vehicle (a), and of a part (b).

"non-road" points is used to better fix the size and position of the AOI.

V. Obstacle hypothesis validation

Whenever an object hypothesis is formulated within the AOI, that "non-road" region is analyzed in order to understand if it denotes an actual obstacle, namely a vehicle, or a false alarm, as shadows or signs on the road.

Since in the AOI only the back of a vehicle is seen, parts such as the rear window, the hatchback, the bumper, and the number plate, are looked for to detect and recognize the vehicle.

Although the shape and the spatial relationships between these parts can be easily described for generic vehicles, their size and their detectable details change substantially according to the distance from the camera and to the resolution of the vision system. Then, a dynamic model is used to direct the search. The parts of a vehicle are represented as nodes in a semantic net, with arcs between the nodes representing *over*, *under*, *adjacent* and *inside* structural relationships (figure 2a). Parts are included in the net depending on the distance at which the vehicle is seen, then the complexity of the net grows while the vehicle approaches. In particular, the model of distant vehicles is described by three nodes: the rear window, the hatchback and the shadow between the rear wheels; while the model of a close vehicle includes more details, such as a node representing the number plate.

Because all these parts appear approximately as rectangles, they can be mainly pointed out by horizontal and vertical contours. Each part is, therefore, represented by a boundary graph, in which four nodes represent the four sides and arcs specify their *top*, *bottom*, *left*, and *right* relationships (figure 2b). Also this graph is dynamic, in fact each part is described by different structures according to the distance of the vehicle. The shape of a part can be completely seen when a vehicle is near, and then it can be modeled as a rectangle. Instead, at a medium distance only the horizontal longer sides can be perceived, then the model turns into two parallel lines. Finally, when the vehicle is very distant, the sides of a part are merged into a single horizontal line.

So straight edge segments are the main features used for obstacle recognition. As soon as an obstacle hypothesis is formulated in the AOI, its distance from the camera is evaluated, supposing that the road is flat and using the approximated relation

$$d = h / \tan(\alpha + \arctan((y_0 - y)/f))$$

where h is the height of the camera from the road surface, α is the elevation angle of the camera with respect to the horizontal plane, f is the focal length of the camera, y_0 and

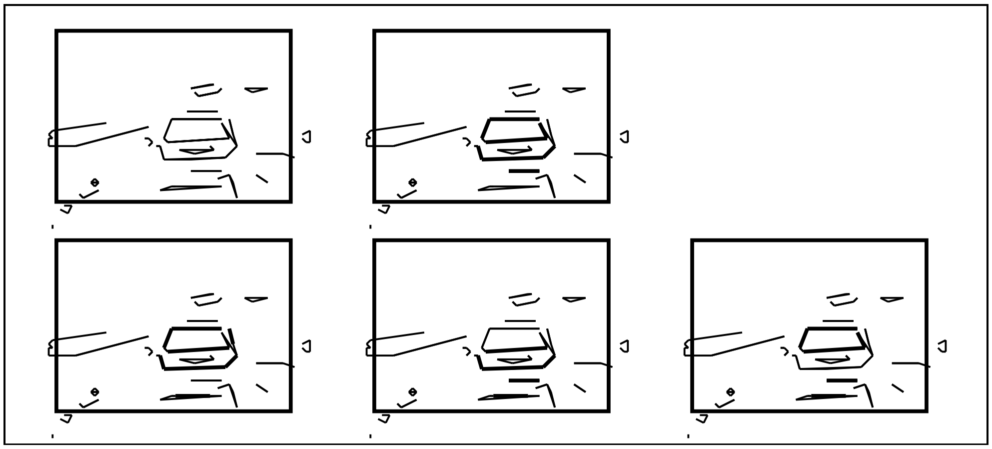


Fig. 3. Possible groupings of the segments in a AOI.

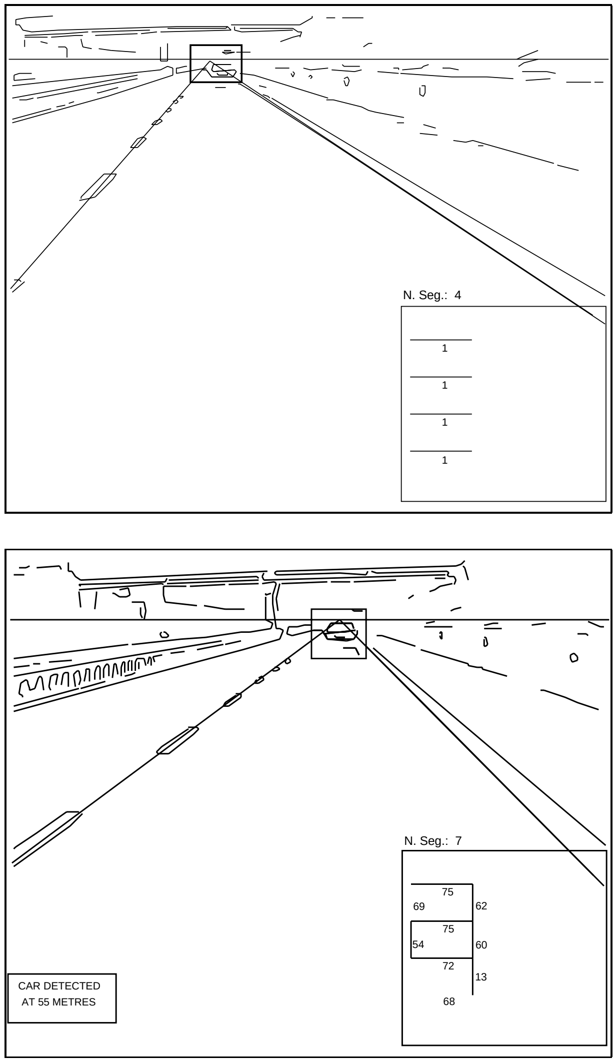
y are the ordinates of the image center and of the base of the AOI respectively. Such distance defines the model to be used. As overtaking vehicles are not considered, obstacles usually appear at the end of the road and the far-away model is used. Therefore, groups of horizontal segments are looked for to single out the presence of a meaningful structure having a probability to correspond to a vehicle. Instead, at a medium and close distance, groups of segments arranged in L, C or closed shapes and satisfying the relationships required by the appropriate model are pointed out.

In particular, in each image of the sequence, from a set of initial candidate segments detected in the AOI, the algorithm considers all possible groupings of the segments according to the model (fig. 3). Because of the cluttered background and of segmentation errors, many sets of segments can match the model. Then a search tree is generated, in which segments are the nodes. Each node of the tree is expanded pointing to all the segments which can be added to that structure. Segments corresponding to a part (i.e. a rectangle) are searched in the following order: the first horizontal segment in the top of the AOI is supposed to be the *top* side of the rectangle, then parallel segments under it are possible *bottom* sides, and nearly vertical segments between the two previous ones are probable *left* and *right* sides.

Each path from the root to each leaf is a possible match with the model, that is an obstacle hypothesis. The best hypothesis H is chosen according to a *completeness factor* and a *closure measure* associated to each match. The completeness factor expresses how well the set of segments represents the complete geometry of the structure, that is how many sides of the rectangle have been identified. The closure measure signifies how much the structure is compact, taking into account its area and the gaps between the extrema of the segments.

Even if the semantic model allows the recognition of vehicles of different types (such as car, vans, and lorries), physical knowledge about specific vehicles (for example, the dimensional ratios between the parts) is used to adjust the aspect of the model in the image. Such integration greatly improves the search and the correctness of the best hypothesis.

However, the obstacle hypotheses formulated frame by frame are hardly reliable enough to be regarded as validated. On the analogy of the human visual persistence, time integration is used to improve such reliability. Because of the apparent slow motion on the image plane of far away obstacles, edges corresponding to parts of the vehicle can be tracked along the sequence while the misleading structures due to the background are lost either because of the head-



a

b

Fig. 4. (a) Obstacle hypothesis formulation. (b) Obstacle detection.

ing changes of the camera when the road bends or because of the perspective enlargements. So only the structures which can be tracked allow the validation of obstacles to verify their consistence and those segments that really belong to the hypothesized obstacle are pointed out. In particular, a *persistence factor*, pf, is associated to each segment of the model. It records how many times a model element has been matched by the best hypotheses H formulated along the sequence. When the pf of all the model elements reaches a prefixed value, the hypothesis active at the present frame is considered as validated and a warning is given about the presence of an obstacle.

VI. RESULTS

The proposed system has been tested on sequences of video images, taken with a B/W CCD camera (2/3" sensor and 16 mm lens) placed on the bonnet of the mobile laboratory MOBLAB [5], 1.40 m height. The image sequences have been sub-sampled in frequency and time to avoid motion interlace effects. The resulting image size is 340 x 280 pixel at a repetition rate of 25 images/s.

Figure 4 shows the case where the supervised vehicle is approaching a slower station wagon. An obstacle hypothesis is fired when the vehicle is at 70 m (fig. 4a), while the warning message is issued at 55 m (fig. 4b). The relative speed The obstacle detection algorithm requires about 80 frames, being the relative speed of 30 km/h.

Even if the proposed algorithm is quite simple, in order to satisfy the real time requirements, the identification criteria are sufficient to warn a driver even if the actual type of vehicle has not been recognized. This can be considered a satisfactory result for a computer vision system devoted to driving assistance of vehicles.

Acknowledgments

This work has been carried on funded by a grant from National Project on Transports (CNR 97.00307.PF74).

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