Boston College Computer Science Department Technical Report BCCS-98-01 (June 1998)
Appears in *1998 IEEE International Conference on Intelligent Vehicles, Stuttgart, Germany, October 1998.*

Highway Scene Analysis from a Moving Vehicle under Reduced Visibility Conditions

Margrit Betke* and Huan Nguyen
Computer Science Department
Boston College
Chestnut Hill, MA 02167-3808

ABSTRACT

This paper describes and evaluates a real-time vision system that detects and tracks vehicles on highways under reduced visibility conditions. The system uses a forward looking video camera in a moving car to estimate the distances of the car to other vehicles on the road. Results of experiments on images sequences in difficult visibility conditions are presented.

1 Introduction

Vision systems that automatically analyze highway scenes from a moving vehicle have been remarkably successful in fair weather conditions (see, for example, [2, 3, 4, 6, 7, 8, 11, 12, 13]). Reliability of these systems, however, is also required for reduced visibility conditions that are due to rainy or snowy weather, tunnels and underpasses, and driving at night, dusk and dawn. Changes in road appearance due to weather conditions have been addressed for a stationary vision system that detects and tracks vehicles, for example, in Ref. [10]. Reference [9] describes how visibility estimates lead to reliable lane tracking from a moving vehicle.

Our initial system for highway scene analysis, introduced in Ref. [1], failed in reduced visibility conditions, heavy traffic, and on highways with cluttered roadsides. Our new system overcomes some of these problems by analyzing the whole highway scene, in particular, by determining the visibility conditions, segmenting the road using color information, and then recognizing and tracking lane markings, road boundaries and multiple cars on the road. Our vision system does not need any initialization by a human operator, but recognizes the cars it tracks automatically. The video data is processed in real time without any specialized hardware. All we need is an ordinary video camera and a low-cost PC with an image capture board.

2 Vision system overview

The input data of the vision system consists of color image sequences taken from a camera mounted inside our car, just behind the windshield. The images show the environment in front of the car – the road, other cars, bridges, and trees next to the road. The primary task of the system is to distinguish the cars from other stationary and moving objects in the images and recognize them as cars. The vision system outputs an online description of road parameters and locations and sizes of other vehicles in the images. This description is then used to estimate the positions of the vehicles in the environment and their distances from the camera-assisted car. The vision system contains four main components: the car detector, the road

*Email: betke@cs.bc.edu

detector, the tracker, and the process coordinator (see Figure 1). Refs. [1, 2] provide the details of earlier versions of the system.

The road detector determines if the images are taken at daytime or night, including tunnel or snow conditions, and then finds the road boundary and lane markings. Its outputs are used by the car detector to steer the search for potential cars within each image frame. Once the car detector recognizes a potential car, the process coordinator creates a tracking process for it and provides the tracker with information about the size and location of the potential car. For each tracking process, the tracker analyzes the history of the tracked areas in the previous image frames and determines how likely it is that the area in the current image contains a car. If it contains a car with high probability, the tracker outputs the distance to the car.

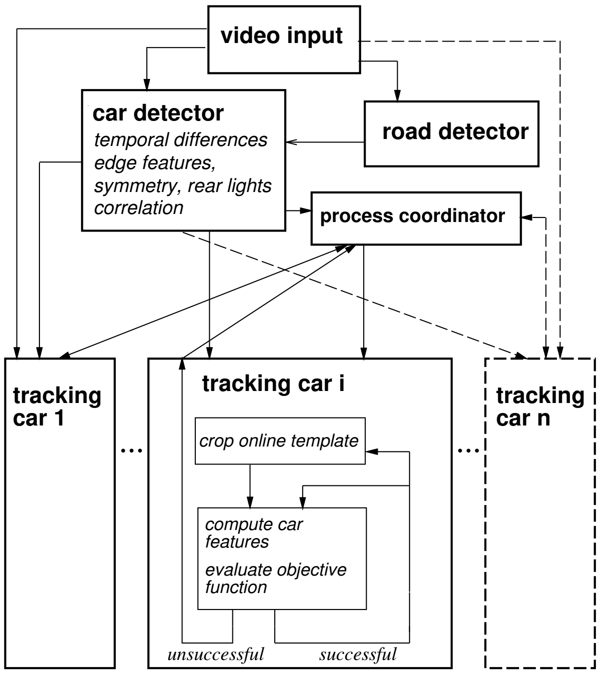

Figure 1: The real-time vision system.

3 Vehicle Detection and Tracking

Our system detects vehicles in the input video by analyzing the motion information provided by multiple consecutive image frames and the color components, edge features, correlation and symmetry in single frames. The system also makes use of prior knowledge of vehicle and road appearances, for example, vehicle shapes and road color. References [1, 2] describe our methods in detail. We provide a summary of detection and tracking tools here:

- Temporal differences of consecutive image frames and estimates of sizes and speeds of cars passing the camera-assisted car from behind are used for initial passing car detection.
- Vehicles in the far distance usually show very little relative motion between themselves and the camera-assisted car, so that temporal methods fail to detect them. Feature-based methods are therefore used instead, which analyze horizontal and vertical edge projections.
- Given only one or two images, it is very difficult to automatically recognize that an image region is indeed containing a vehicle (often only part of the vehicle is caught). The vision system therefore employs its tracking capabilities to recognize if the imaged object is a vehicle.
- The system crops tracked objects from the scene and uses them as online models to create templates. These templates are resized and matched online using the normalized correlation coefficient. In addition, the symmetry of the tracked objects is exploited.
- Due to the strong up-and-down motion of the video camera in the camera-assisted car, tracking windows are adjusted adaptively.
- Road boundaries and lane markings are detected in each frame by a spatial recursive least squares filter [5].
- A statistical model for "road color" is computed offline, which is then used online to

classify the pixels that image the road and to discriminate them from pixels that image obstacles such as other vehicles.

In addition, a statistical model for "daytime sky color" is computed offline and used online to distinguish daytime scenes from tunnel and night scenes. Detecting the rear lights of a tracked object, as described in the following paragraph, provides additional information that the system uses to identify the object as a vehicle. This is benefical in particular for reduced visibility driving, e.g. in a tunnel, at night or in snowy conditions.

3.1 Rear light detection

The rear light detection algorithm searches for bright spots in image regions that are most likely to contain rear lights, in particular, the middle 3/5 and near the sides of the tracking windows. To reduce the search time, only the red component of each image frame is analyzed, which is sufficient for rear light detection.

The algorithm detects the rear lights by looking for a pair of bright pixel values in the tracking window that exceeds a certain threshold. To find this pair and the centroid of each light, the algorithm exploits the symmetry of the rear lights with respect to the vertical axis of the tracking window. It can therefore eliminate false rear light candidates that are due to other effects, such as specular reflections or lights in the background.

For windows that track cars at less than 10m distance, a threshold that is very close to the brightest possible value 255, e.g. 250, is used, because at such small distances bright rear lights cause "blooming effects" in CCD cameras, especially in poorly lit highway scenes, at night or in tunnels. For smaller tracking windows that contain cars at more than 10m distance, a lower threshold of 200 was chosen experimentally.

Note that we cannot distinguish rear light and rear break light detection, because the position of the rear lights and the rear break lights on a car need not be separated in the US. This means that our algorithm finds either rear lights (if turned on) or rear break lights (when used). Figures 2 and 3 illustrate rear light detection results for typical scenes.

3.2 Distance Estimation

The perspective projection equations for a pin hole camera model are used to obtain distance estimates. The coordinate origin of the 3D world coordinate system is placed at the pin hole, the X and Y-coordinate axes are parallel to the image coordinate axes x and y, and the Z-axis is placed along the optical axis. Highway lanes usually have negligible slopes along the width of each lane, so we can assume that the camera's pitch angle is zero if placed horizontally level on the dashboard. If the camera is also placed at zero roll and yaw angles, the actual roll angle depends on the slope along the length of the lane and the actual yaw angle depends on the lane's curvature. Given conversion factors c_{horiz} and c_{vert} from pixels to mm for our camera and estimates of the width W and height H of a typical car, we use the perspective equations $Z = c_{horiz} f W/w$ and $Z = c_{vert} f H/h$, where Z is the distance between the camera-assisted car and the car that is being tracked in meters, w is the car width and h the car height in pixels, and f is the focal length in mm. Given our assumptions, the distance estimates are most reliable for typically sized cars that are tracked immediately in front of the camera-assisted car.

4 Experimental Results

The analzed data consists of RGB video taken on American highways and city expressways at daytime and at night. The city expressway data included several tunnel sequences. Figure 2 and

Figure 3 show results for sequences in reduced visiblity due to snow, night driving, and tunnel.

5 Conclusions

We have presented a real-time vision system that detects and tracks vehicles on highways under reduced visibility conditions. The system works well on snowy highways, at night when the background is uniformly dark, and in certain tunnels. However, at night on city expressways, when there are many city lights in the background, the system has problems finding vehicle outlines and distinguishing vehicles on the road from obstacles in the background. Traffic congestion worsens the problem. However, even in these extremely difficult conditions, the system usually finds and track the cars that are directly in front of the camera-assisted car and only misses or misidentifies the sizes of the cars in adjacent lanes. A more precise 3D-world model of the adjacent lanes and the highway background than the one that we incorporated into the system should yield more reliable results in these difficult conditions.

Acknowledgements

Earlier versions of the system were developed at the University of Maryland in joint work. The first author thanks her former collaborators Esin Haritaoglu and Larry Davis for their efforts and support. The authors also thank Dewin Chandra, Boston College, for helping to collect and digitize the data presented here.

References

[1] M. Betke, E. Haritaoglu, and L. Davis. Multiple vehicle detection and tracking in hard real time. In *Intelligent Vehicles*, pages 351–356, 1996. Also UMD CAR-TR-858, http://www.cfar.umd.edu:80/ftp/TRs/CVL-Reports-1996/TR3667-Betke.ps.gz.

[2] M. Betke, E. Haritaoglu, and L. Davis. Highway scene analysis in hard real time. In *IEEE Conf on Intelligent Transportation Systems*, Boston, 1997.

[3] U. Franke and I. Kutzbach. Fast stereo based object detection for stop & go traffic. In *Intelligent Vehicles*, pages 339–344, 1996.

[4] V. Graefe and W. Efenberger. A novel approach for the detection of vehicles on freeways by real-time vision. In *Intelligent Vehicles*, pages 363–368, 1996.

[5] S. Haykin. *Adaptive Filter Theory.* Prentice Hall, 1991.

[6] L. Kaminski, J. Allen, I. Masaki, and G. Lemus. A sub-pixel stereo vision system for cost-effective intelligent vehicle applications. In *Intelligent Vehicles*, pages 7–12, 1995.

[7] Q. Luong, J. Weber, D. Koller, and J. Malik. An integrated stereo-based approach to automatic vehicle guidance. In *ICCV*, pages 52–57, 1995.

[8] M. Maurer, R. Behringer, S. Fürst, F. Thomarek, and E. D. Dickmanns. A compact vision system for road vehicle guidance. In *ICPR*, volume 3, pages 313–317, 1996.

[9] D. Pomerleau. Visibility estimation from a moving vehicle using the RALPH vision system. In *Conf. Intelligent Transportation Systems*, page 403. IEEE, 1997.

[10] J.C. Rojas and J. D. Crisman. Vehicle detection in color images. In *Intelligent Transportation Systems*, Boston, MA, 1997. IEEE.

[11] S. M. Smith. ASSET-2: Real-time motion segmentation and shape tracking. In *ICCV*, pages 237–244, Cambridge, MA, 1995.

[12] F. Thomanek, E. D. Dickmanns, and D. Dickmanns. Multiple object recognition and scene interpretation for autonomous road vehicle guidance. In *Intelligent Vehicles*, pages 231–236, 1994.

[13] T. Zielke, M. Brauckmann, and W. von Seelen. Intensity and edge-based symmetry detection with an application to car-following. *CVGIP: Image Understanding*, 58:177–190, 1993.

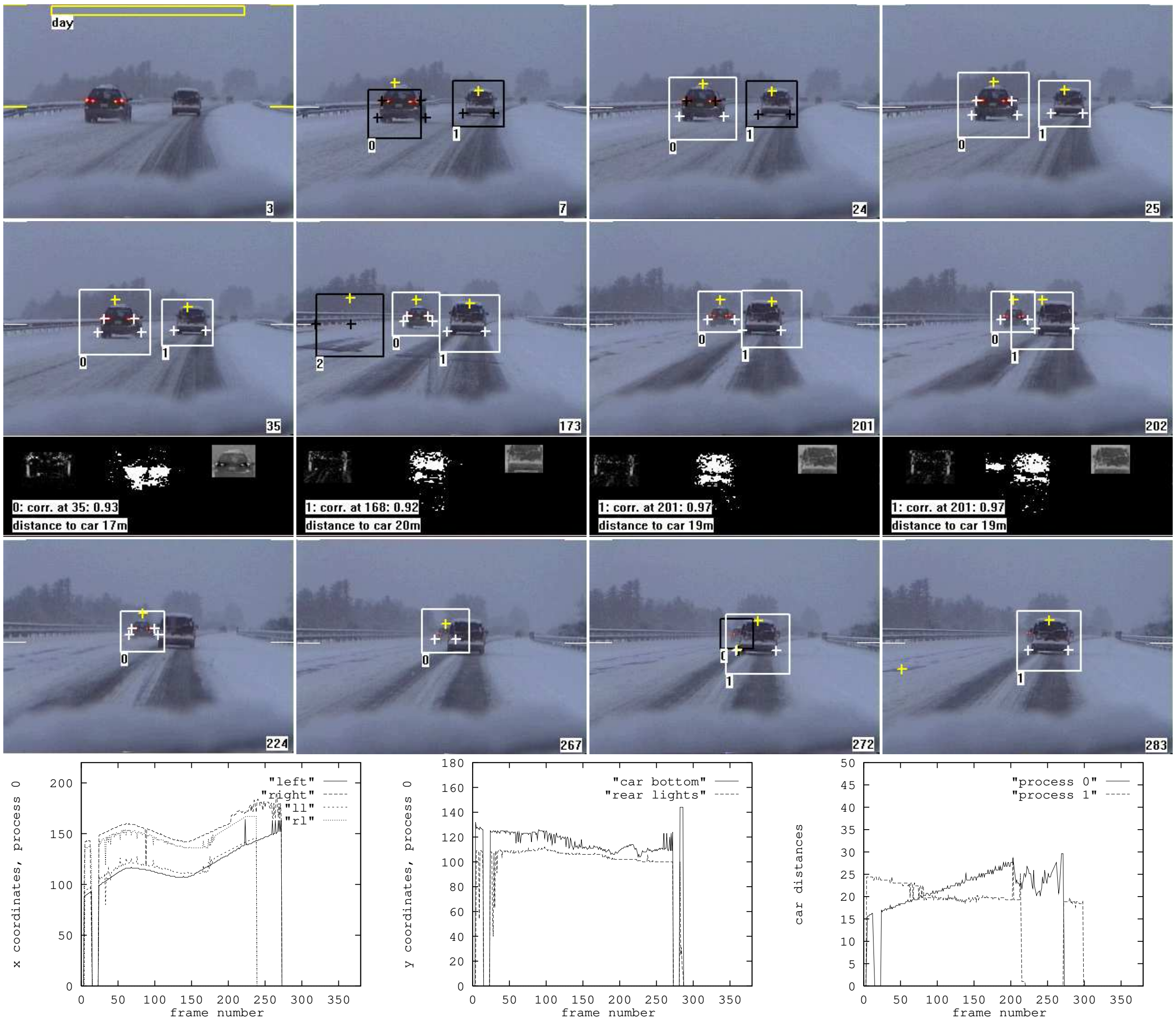

Figure 2: Detecting and tracking two cars on a snowy highway. The images are shown with their frame numbers in their lower right corners. In frame 3, the system determines that the data is taken at daytime. The black rectangles show regions within which moving objects are detected. Yellow crosses indicate the top of the cars and white crosses indicate the bottom left and right car corners and rear light positions. The rectangles and crosses turn white when the system recognizes these objects to be cars. Underneath the middle image row, one of the tracking processes is illustrated in three ways: on the left, the vertical edge map of the tracked window is shown, in the middle, pixels identified not to belong to the road, but instead to an obstacle, are shown in white, and on the right, the most recent template used to compute the normalized correlation is shown. The text underneath shows the most recent correlation coefficient and distance estimate. The three graphs underneath the image sequence show position estimates. The left graph shows the x-coordinates of the left and right side of the left tracked car ("left" and "right") and the x-coordinates of its left and right rear lights ("ll" and "rl"). The middle graph shows the y-coordinates of the bottom side of the left tracked car ("car bottom") and the y-coordinates of its left and right rear lights ("rear lights"). The right graph shows the distance estimates for both cars.

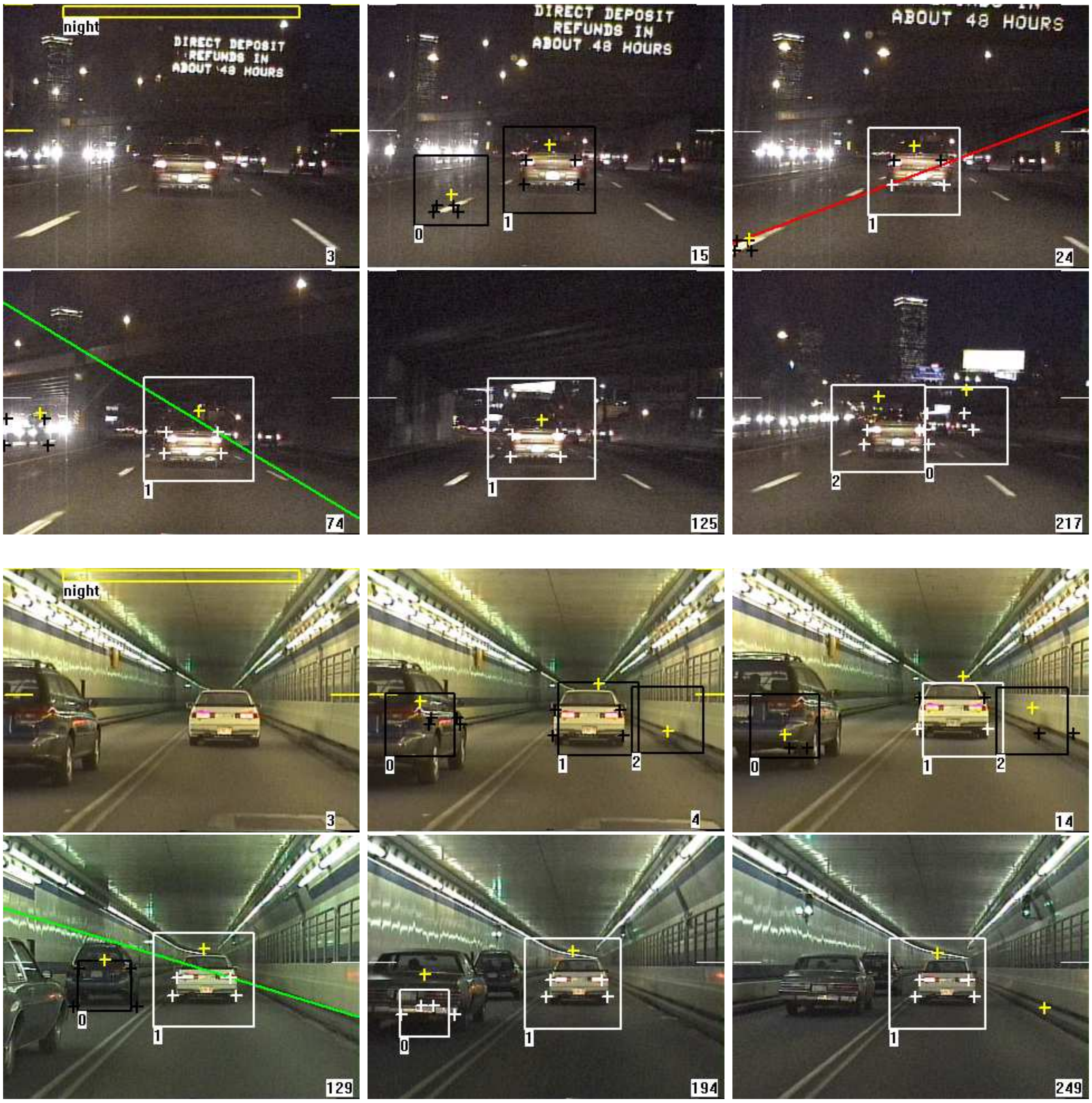

Figure 3: Detecting and tracking cars at night and in a tunnel (see caption of previous figure for color code). The cars in front of the camera-assisted car are detected and tracked reliably. The front car is detected and identified as a car at frame 24 and tracked until frame 260 in the night sequence, and identified at frame 14 and tracked until frame 258 in the tunnel sequence. The size of the cars in the other lanes are not detected correctly (frame 217 in night sequence and frame 194 in tunnel sequence).