A Monocular Solution to Vision-based ACC in Road Vehicles

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Abstract. This paper describes a monocular vision-based Adaptive Cruise Control (ACC) System in the framework of Intelligent Transportation Systems (ITS) technologies. The challenge is to use a single camera as input, in order to achieve a low cost final system that meets the requirements needed to undertake serial production.

1 Introduction

A monocular imaging device (a single FireWire digital camera) is deployed to provide "indirect range" measurements using the laws of perspective. Some previous developments use available sensing methods such as radar [1], stereo vision [2], or a combination of both [3]. Only a few works deal with the problem of monocular vehicle detection using symmetry and color features [4], or pattern recognition techniques [5]. In the current work, the searching space is reduced in an intelligent manner in order to increase the performance of the detection module. Accordingly, road lane markings are detected and used as the guidelines that drive the vehicle searching process. The area contained by the limits of the lanes is scanned in order to find vehicle candidates that are passed on to the vehicle recognition module. This helps reduce the rate of false positive detections. In case that no lane markings are detected, a basic *area of interest* is used instead covering the front part ahead of the ego-vehicle. The description of the lane marking and vehicle detection systems is provided below, together with some graphical results.

2 System Description

Lane Tracking

The system is divided in three modular subsystems with specific functions. The first subsystem is responsible for lane detection and tracking, as well as lane crossing monitoring. Images obtained from the camera are processed and clothoid curves are fitted to the detected markings. The algorithm scans up to 25 lines in the *area of interest*, from 2 meters in front of the camera position to below the horizon. The developed algorithm implements a non-uniform spacing search that reduces certain unstabilities in the fitted curve. The final state vector is composed of 6 variables [7] for each line on the road: c_{oh}, c_{1h}, c_{ov}, c_{1v}, x_o, P_o, where c_{oh} and c_{1h} represent the clothoid horizontal curvature parameters, c_{ov} and c_{1v} stand for the clothoid vertical curvature parameters, while x_o and P_o are the lateral error and orientation error, respectively, with regard to the centre of the lane. The clothoid curves are then estimated based on lane marking measurements using a Kalman filter for each line. These lines conform the *area of interest.* Figure 1 depicts a sequence of images in which the result of the lane tracking algorithm is overprinted on the road images.

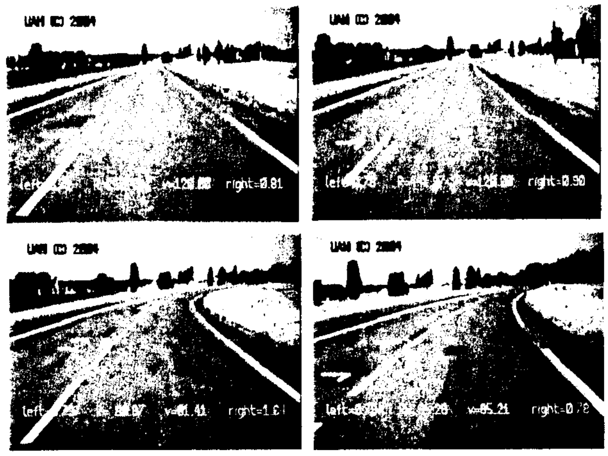

Fig. 1. Lane tracking example in a sequence of images. The green lines represent the estimated lines of the road. The example also depicts the error between the left wheel of the car the the left lane (left), the error between the right wheel of the car and the right lane (right), the radious of curvature of the road estimated at a lookahead distance of 50m (R), and the maximum recommended velocity to bend the curve (V) according to the radious of curvature.

Car Detection and Recognition

The area of the image contained between the lines that represent the lane is scanned in order to look for candidate vehicles along the lane as depicted in figure 2. Car detection is performed in the areas limited by lane markings. Based on charactertics of shape, size and position, among others, candidates are selected. Each one of the candidates is then divided into five different subareas, that are then processed independently. For each subarea of the candidate, a support vector machine (SVM) [6] has been trained, using the tool 'TsetBuilder' we have developed. The areas are validated independently, and another SVM determines whether the outputs of the first

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filter. Figure 3

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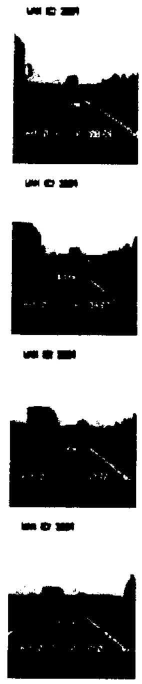

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SVMs represent those of a valid cadidate. Candidates are tracked using a Kalman filter. Figure 3 shows the result of the detection and tracking algoritm.

Fig. 2. Sequential vehicle candidates searching along the detected lane

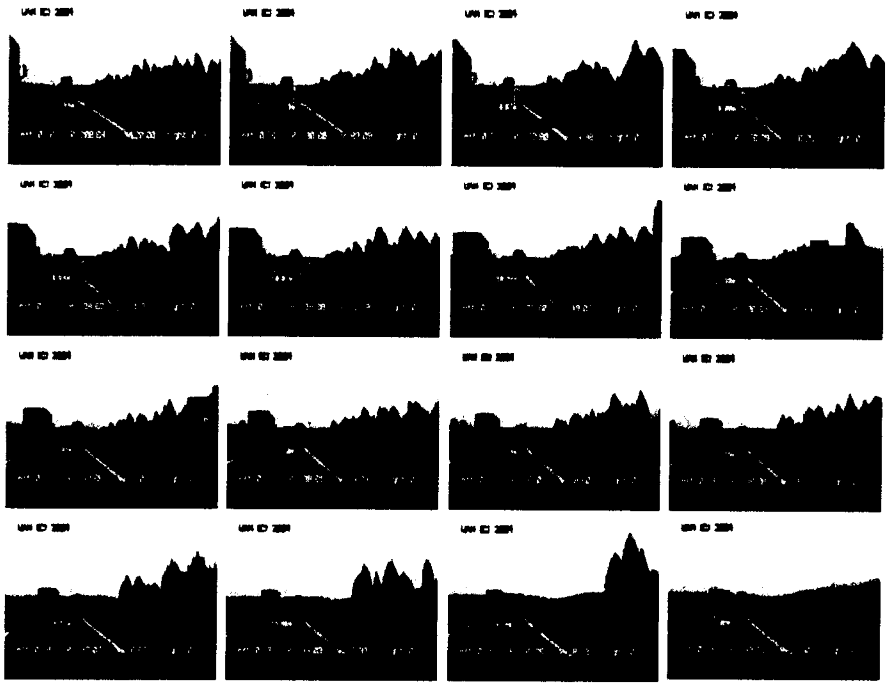

Fig. 3. Vehicle tracking example in a sequence of images.

The distance between the ego-vehicle and the preceding vehicle along the lane becomes the input to the Adaptive Cruise Control System.

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