Review on Automatic Vehicle Driving and Parking using Image Processing and Sensors

Mr. Amit U.Godge[1], Dr. Ulhas B. Shinde[2]
[1]*Research Scholar, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India*
[2]*Principal, CSMSS COE , Aurangabad, Maharashtra, India*

***Abstract*— Today automobile sector is most developing area and it is became important part of human life. With the rapid increase of cars the need to find available parking space in the most efficient manner, to avoid traffic congestion in a parking area, is becoming a necessity in car park management. Current car park management is dependent on either human personnel keeping track of the available car park spaces or a sensor based system that monitors the availability of each car park space or the overall number of available car park spaces. In both situations, the information available was only the total number of car park spaces available and not the actual location available. In addition, the installation and maintenance cost of a sensor based system is dependent on the number of sensors used in a car park. Automatic Vehicle Driving is a generic term used to address a technique aimed at automating entirely or in part one or more driving tasks. The automation of these tasks carries a large number of benefits, such as: a higher exploitation of the road network, lower fuel and energy consumption, and of course improved safety conditions compared to the current scenario. The tasks that automatically driven vehicles are able to perform include the possibility to follow the road and keep within the right lane, maintaining a safe distance between vehicles, regulating the vehicle's speed according to traffic conditions and road characteristics, moving across lanes in order to overtake vehicles and avoid obstacles, helping to find the correct and shortest route to a destination, and the movement and parking within urban environments. Since the potential of soft-computing for driver assistance systems has been recognized, much effort has been spent in the development of appropriate techniques for robust lane detection, object classification, tracking, and representation of task relevant objects.**

***Index Terms*— Automation, Tracking, Automatic Vehicle Driving, Lane Detection.**

I. INTRODUCTION

Behaviour Planning for Intelligent Vehicles

Vehicle Intelligence systems aim at increasing the comfort and safety of traffic participants by sensing the environment, analyzing the situation and signaling relevant information to the driver. In order to reliably accomplish this demanding task, the information of different sensors must be evaluated and fused to obtain a suitable representation of the traffic situation. The complexity of the whole data processing architecture is determined by actual task the Vehicle Intelligence system is devoted to. Among others, these tasks include lane departure warning, lane keeping, collision warning or avoidance, adaptive cruise control, and low speed automation in congested traffic.

A Steps for intelligent vehicle Behavior-

a. Pre-processing,

b. Domain Specific Processing,

a. Pre-processing-

In this segment the intelligent vehicle will be undergoing following steps to decide the behavior and to interpret surrounding it. it is demonstrated how the combination of domain knowledge, imbedded by a exible road lane estimation mechanism and the coupling with object detection modules, exploiting temporal redundancies, yield accurate descriptions of scene elements. The image features calculated in the pre-processing stage should be meaningful and accurately estimated, while computation time is restricted. To meet this requirement we compute a pixel mask, to which the subsequent image processing operations will be restricted. This mask is obtained by adaptive thresholding of an estimated entropy image. By applying the pixel mask it efficiently calculate local image orientations and line-segments on the basis of a Canny-Edge-Detector. The line-segments are obtained by clustering pixel chains having identical orientations. Each segment is characterized by the pixel coordinates of its end-points and the mean gradient along that segment, and therefore it provides a sparse coding of the image contours. The calculation of these high level features are beneficial for at least two important reasons: On the hand the development of the task specific modules based on these features is significantly simplified, and on the other hand they are less sensitive to varying lightning conditions and noise. Even the computation required for the whole image processing can be reduced, due to less costly processing in the higher-level modules, as demonstrated further below.

b. Domain Specific Processing-

In this section vehicle will detect its position on the road and the lane which it is using, it will access the moving and the rigid objects in its surrounding. And it will take the images of the particulars and access it's containing so that to take decision for parking in particular on pedestrian recognition in urban environments. In this work on how to incorporate domain knowledge into the interpretation process of segmentation results, here based on colour features. Vehicle Detection in vision based driver assistance systems the vehicle detection task is usually divided in segmentation and a subsequent tracking stage. Obviously, the results obtained by segmentation algorithms and the tracking module are not independent. Therefore, a coupling architecture, aiming to suppress false detections and thereby to increase the reliability of the whole vehicle detection stage. In this system it implemented two different vehicle segmentation algorithms, which are based on different image features. The first segmentation algorithm employs the line segments calculated in the pre-processing stage for generating a list of potential vehicle positions. The middle of each approximately horizontal segment serves as a starting position for searching lateral vehicle borders. Two signals are calculated by vertical

Projecting image and gradient data in an image area defined by the line-segment and the expected height of the vehicle. The lateral borders of a potential vehicle are determined by thresholding the signals obtained by the projection. If the vehicle's width matches the expected width at the given image position (estimated in the lane-detection module), the ROI (region of interest) is accepted. The second strategy for detecting potential vehicle positions utilizes the lane border estimates, i.e., is based on higher-level knowledge. The outline of the algorithm is as follows: Each lane is scanned from the lowest image row to a certain vertical coordinate that corresponds to a predefined maximal distance in the world. Potential vertical vehicle positions are obtained if a certain number of pixels in a row (delimited by the lane borders) exceed a significant vertical gradient level. In order to accept or to reject the hypotheses obtained by scanning the rows, the same test for lateral vehicle borders as in the segmentation module is performed. It takes advantage of the redundant information provided by the different segmentation algorithms by temporal integration and coupling with an object tracker. The tracker we employ is based on the Hausdorfi-Distance and is described in detail. But instead of calculating the distance transform on the basis of the features as given in the corner image obtained in the pre-processing stage is used.

II DETECTION MECHANISM

A. Lane Detection

A number of tasks such as lane departure warning and lane following rely on the information about the vehicle's position relative to the lane boundaries. Reasonable approaches to lane-detection have to incorporate a bottom-up process detecting new lane borders and a lane tracking process based on the previously detected lane positions. In order to efficiently perform the bottom-up process, it utilizes the line-segments for generating lane hypotheses. To remove the effects induced by the perspective projection, the line-segments pointing to an estimated vanishing point are transformed to world coordinates. A list of lane hypotheses is generated by evaluating projections of the transformed line-segments onto the horizontal world coordinate axis. The coupling between the bottom-up lane detection and the tracking mechanism is effectively carried out at the hypotheses level. Each potential lane position is detected

B. Detection of Non Rigid Objects

In recent years, not much attention has been given to image processing approaches aimed at increasing the safety of more passive and exposed traffic participants such as pedestrians and motorcyclists, respectively, in urban environments. A major goal is to perform a judgment on object behavior to forestall collision of a moving observer equipped with such a driver assistant system. The work presented here addresses the localization of pedestrians.

C. Pedestrian recognition

The initial detection and the tracking of pedestrians in urban environments face several problems such as cluttered backgrounds, roads in bad condition and large object movements. The objects themselves are non-rigid and can change their appearance on a very short time scale. Also highly varying pose, self-occlusion and the occurrence of pedestrians in groups call for new object representations

D. Symmetry Detection

In this approach, image features are chosen very carefully under the aspects of generality and simplicity. They should be invariant under a wide range of conditions so that the same detection and tracking framework will function

well in a broad variety of situations. Also in an effort to make object detection and tracking as efficient as possible the features should be easy to extract. In addition, this new symmetry operator brings together the ideas of representing the image data compactly by means of skeletonization with continuous edge information and also in the same run to encode also gray scale colour and form information. Therefore, a local symmetry detector has been developed, which compactly encodes and groups locally symmetric image structure. This attention like processing step of the system allows a very rapid scene analysis for further processing steps of higher resolution.

E. Context-Based Object Detection

In this section, a general, domain-independent, stochastic model-based approach for an automated scene analysis is presented. The approach consists of an initial segmentation, in which the image is divided into a set of disjoint regions based on their respective colour values and a subsequent joint classification where the generated image regions are assigned to object classes. To improve reliability the classification process is performed as a fusion of sensor information and symbolic information. Context knowledge, defined as knowledge about the spatial relationships between the different object classes, is used as an example for symbolic information. It provide a general framework to carry out the fusion in a systematic, unified way including a methodology of expressing symbolic information analytically with the help of Markov random field theory.

F. Joint classification

The goal of the classification process is to assign one of a predefined number of object classes to every image region. In addition to sensor information in the form of extracted regional features like colour, size or texture, symbolic information is used to generate the assignment. In this approach the classification is formulated as an optimization problem using a maximum a posterior estimation rule. The classification criteria are combined using the Bayesian theorem, where feature measurements and symbolic information are coded as conditional probability and a-priori probability, respectively. Several strategies exist for deriving a probabilistic expression coding the assignment dependent on the feature measurements.

III. INTELLIGENT VEHICLE HANDLING: STEERING AND BODY POSTURES WHILE CORNERING

Vehicle handling and control is an essential aspect of intelligent driver assistance systems, a building block of the upcoming generation of "*Intelligent cars*". A car's handling is affected by

(*i*) *Technological* (engine, suspension, brakes, tires, wheels, steering, etc.),

(*ii*) *Environmental* (road condition, weather, traffic, etc.), and

(*iii*) *Human* (attentiveness, reactivates, driver agility, etc.)factors and their mutual interrelationship. In this paper we investigate on how a driver's endeavour for precise steering interferes with lateral acceleration while cornering. Depending on the steering ratio and the cruising speed, we identify that the readiness of a driver to compensate lateral forces exhibits counterintuitive characteristics. A driver body posture recognition technique based on a high resolution pressure sensor integrated invisibly and unobtrusively into the fabric of the driver seat has been developed. Sensor data, collected by two 32x32 pressure sensor arrays (seat- and backrest), is classified according to features defined based on cornering driving situations.

A. Image processing system

The fusion of different sensor information and pre-processing results increases the performance of the system. The basic methods are specialized for a specific kind of sensor information. In addition, it speeds up computation time for real time applications. The feature we most often employ for this purpose is called local orientation coding. In the field F2, we use motion detection algorithms segmenting overtaking and overtaken vehicles. In contrast to algorithms in different vision fields, we use a pattern tracking based algorithm, which ensures high stability. The long distance field F3 is analyzed by texture-based methods. The low spatial resolution makes edge-based processing infeasible.

B. The basic algorithms

The algorithms providing partial solutions for object detection, tracking and classification have been incorporated into driver assistance architecture. The following enumeration gives an overview over the applied methods:

a. *Initial object detection:* local orientation coding polygon approximation of contours, use of local symmetry, pattern motion analysis, and texture analysis based on local image entropy, local variance analysis, local co-occurrence measures, shadow analysis, colour analysis, and radar mapping.
b. Object tracking: Hausdorff distance matching, parametric optimization, and cross entropy.

c. Object classification: local orientation classifier, Hausdorff distance classifier, co-occurrence classifier, and parametric optimization classifier. The algorithms can be classified as working on differential information (e.g. edges) or integral measurements (e.g. texture).

d. Initial object detection

The main motivation of using multiple simple methods is that the design of a single method suitable for all conceivable scenarios seems to be impossible. Therefore, in order to provide reliable results and to ensure a fast and robust processing, a coupling of *specialists* is implemented. The three methods used in the real time implementation, will now be described. An integration of a differential algorithm (local orientation coding), an integrative algorithm (local image entropy) and a shadow analysis method (model-based) in the real-time system is done.

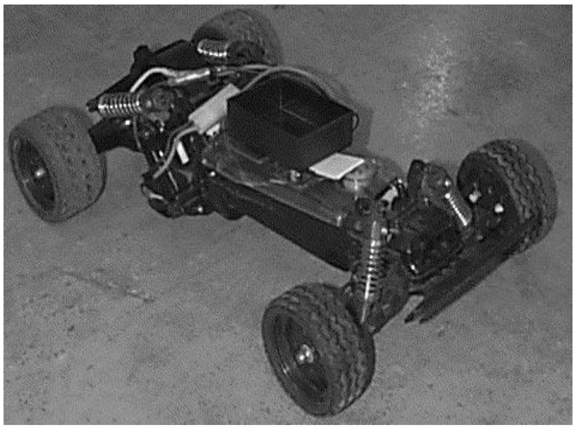
IV. AUTONOMOUS VEHICLE CONTROL USING IMAGE PROCESSING

Unlike other projects in the area of telerobotic control or automated vehicles, the main focus in this project was not to make the vehicle and its supporting infrastructure as sophisticated as possible by using high-end technology like parallel computers, image processing chips and so on, but instead as it is stated in the acronym for FLASH, to make such a vehicle as cheap, easy to build, and easy to modify as possible. This approach allows experimentation with a number of similar model vehicles, each worth less than $1000 in hardware.

A. The Basic Frame for the Vehicle

The basic framework used for the vehicle is a model of an all-terrain (dune buggy) remote control car in the scale 1:15. In this case, a model from TAMIYA was used. Such cars are available in hobby stores like Radio Shack for less than $100.1 Therefore; this toy model car provides an inexpensive chassis for the additions necessary in order to make it capable for telerobotic and automatic mode.

In fact, any type of model vehicle could have been chosen for our purpose, since they all have similar features. Choosing an off-road all-terrain vehicle has the advantage of a very robust design. The vehicle is equipped with a standard 6V DC motor that drives the rear wheels. With this motor, it is capable of speeds up to 10 MPH. Different speeds for the motor are achieved by using a pulse-width-modulation (PWM) of the motor voltage. The PWM signal is created in the motor-control unit (MCU) that is located on the same circuit board as the receiver electronics. The front wheels have a mechanical connection to a standard RC steering servo that is also controlled by PWM signals. This servo makes it possible to move the front wheels to an angle of about 35o to both sides. By using two different PWM signals, it is therefore possible to control both the longitudinal and the lateral behavior of the model vehicle. One modification that was immediately applied to all model vehicles used in the FLASH-Lab is replacing the plastic off-road tires by low-profile rubber tires that are more suitable for indoor use. The vehicle comes with a standard remote control set. It consists of a hand-held transmitter with potentiometer (variable resistor) type input devices for giving steering and speed commands. On the vehicle it is a circuit board that contains the receiver and the motor-



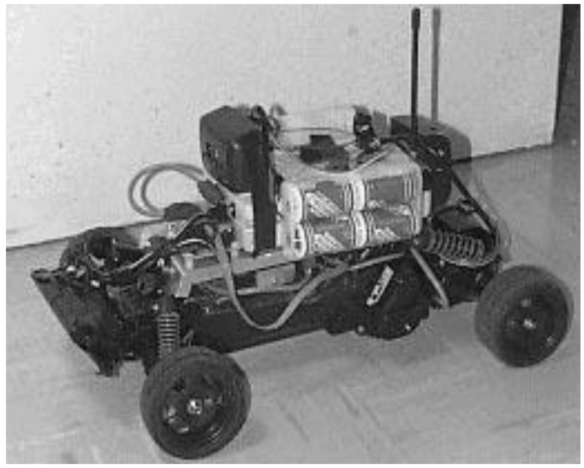
Picture of unmodified / Type I vehicle

Type I Vehicle: RC with Modified Transmitter

The original goal was to make as few modifications to the basic vehicle hardware as possible. The only significant alteration necessary for tele robotic operation is modifying the transmitter part of the remote control, so that it can get its input (the steering commands) from different sources. The original transmitter unit has two potentiometers (variable resistors) that are used to input the desired steering angle and speed. The actual input to the transmitter electronics is the variable resistance and therefore the voltage drop over these two potentiometers.

Type II Vehicle: Serial Link with Microcontroller

The Type II vehicle is an improvement over the Type I design in the sense that it overcomes some of the limitations of the earlier design. This is done by applying the same general type of modifications on the receiver side as were done on the transmitter side on the first design: introducing more hardware in the path of the driving commands to make the execution of these commands more accurate and more flexible.



Picture of Type II vehicle

One part of this hardware modification is to use a microcontroller to interface with the motor-control unit instead of directly connecting it to the receiver. This ensures not only a more precise execution of the commands by generating well-defined signals in the microcontroller, but provides also the ability to make sure that the commands are really executed the way they are should to be (using some form of feedback).

Type III Vehicle: The Microcontroller On-Board the Vehicle

For the on-board computing device, we decided to use the 68HC11 microcontroller from Motorola. The HC11 has been chosen for its simplicity of operation and availability of software. It is used here on a special board from Coactive Aesthetics called the GCB11 It has its own embedded C code functions to simplify the task of programming the system.

VII. CONCLUSION

Although the state of soft-computing applications has improved recently, the development of driver assistance systems remains a challenging task. The difficulty arises from the demand, that such systems must reliably interpret the physical measurements delivered by various sensors and generate the intended behavior on that basis. In order to cope with the resulting complexity such systems must be organized by a modular, hierarchical architecture. It presents a modular architecture defining four levels of data processing, by which an increasing amount of symbolic information is gained sequentially. Image data is main source of information about the environment.

REFERENCE

[1] M. Sugeno and K. Murakami, "An experimental study on fuzzy parking control using a model car," in *Industrial Applications of Fuzzy Control*, M. Sugeno, Ed. Amsterdam, The Netherlands: North-Holland, 1985, pp. 105–124.

[2] M. Sugeno, T. Murofushi, T. Mori, T. Tatematsu, and J. Tanaka, "Fuzzy algorithmic control of a model car by oral instructions," *Fuzzy Sets Syst.*, vol. 32, pp. 207–219, 1989.

[3] M. Ohkita, H. Mitita, M. Miura, and H. Kuono, "Traveling experiment of an autonomous mobile robot for a flush parking," in *Proc. 2nd IEEE Conf. Fuzzy System*, vol. 2, San Francisco, CA, 1993, pp. 327–332.

[4] S. Yasunobu and Y. Murai, "Parking control based on predictive fuzzy control," in *Proc. IEEE Int. Conf. Fuzzy Systems*, vol. 2, 1994, pp. 1338–1341.

[5] W. A. Daxwanger and G. K. Schmidt, "Skill-based visual parking control using neural and fuzzy networks," in *IEEE Int. Conf. Systems, Man, and Cybernetics*, vol. 2, 1995, pp. 1659–1664.

[6] D. Leitch and P. J. Probert, "New techniques for genetic development of a class of fuzzy controllers," *IEEE Trans. Syst., Man, Cybern.*, vol. 28, pp. 112–123, Feb. 1998.

[7] M. C. Leu and T. Q. Kim, "Cell mapping based fuzzy control of car parking," in *Proc. IEEE Int. Conf. Robotics and Automation*, 1998, pp. 2494–2499.

[8] K.Y. Lian, C. S. Chin, and T. S. Chiang, "Parallel parking a car-like robot using fuzzy gain scheduling," in *Proc. 1999 IEEE Int. Conf. Control Applications*, vol. 2, 1999, pp. 1686–1691.

[9] F. Gomez-Bravo, F. Cuesta, and A. Ollero, "Parallel and diagonal parking in nonholonomic autonomous vehicles," *Eng. Applicat. Artif. Intell.*, vol. 14, pp. 419–434, 2001.

[10] B. Shirazi and S. Yih, "Learning to control: a heterogeneous approach," in *Proc. IEEE Int. Symp. Intelligent Control*, 1989.

[11] M. Sugeno and K. Murakami, "An experimental study on fuzzy parking control using a model car," in *Industrial Applications of Fuzzy Control*, M. Sugeno, Ed. Amsterdam, The Netherlands: North-Holland, 1985, pp. 105–124.

[12] M. Sugeno, T. Murofushi, T. Mori, T. Tatematsu, and J. Tanaka, "Fuzzy algorithmic control of a model car by oral instructions," *Fuzzy Sets Syst.*, vol. 32, pp. 207–219, 1989.

[13] M. Ohkita, H. Mitita, M. Miura, and H. Kuono, "Traveling experiment of an autonomous mobile robot for a flush parking," in *Proc. 2nd IEEE Conf. Fuzzy System*, vol. 2, San Francisco, CA, 1993, pp. 327–332.

[14] S. Yasunobu and Y. Murai, "Parking control based on predictive fuzzy control," in *Proc. IEEE Int. Conf. Fuzzy Systems*, vol. 2, 1994, pp. 1338–1341.

[15] W. A. Daxwanger and G. K. Schmidt, "Skill-based visual parking control using neural and fuzzy networks," in *IEEE Int. Conf. Systems, Man, and Cybernetics*, vol. 2, 1995, pp. 1659–1664.

[16] D. Leitch and P. J. Probert, "New techniques for genetic development of a class of fuzzy controllers," *IEEE Trans. Syst., Man, Cybern.*, vol. 28, pp. 112–123, Feb. 1998.

[17] M. C. Leu and T. Q. Kim, "Cell mapping based fuzzy control of car parking," in *Proc. IEEE Int. Conf. Robotics and Automation*, 1998, pp. 2494–2499.

[18] K.Y. Lian, C. S. Chin, and T. S. Chiang, "Parallel parking a car-like robot using fuzzy gain scheduling," in *Proc. 1999 IEEE Int. Conf. Control Applications*, vol. 2, 1999, pp. 1686–1691.

[19] F. Gomez-Bravo, F. Cuesta, and A. Ollero, "Parallel and diagonal parking in nonholonomic autonomous vehicles," *Eng. Applicat. Artif. Intell.*, vol. 14, pp. 419–434, 2001.

[20] B. Shirazi and S. Yih, "Learning to control: a heterogeneous approach," in *Proc. IEEE Int. Symp. Intelligent Control*, 1989, pp. 320–325.