Intelligent Robotic Car for Autonomous Navigation: Platform and System Architecture

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***Abstract*—This paper presents the platform and system architecture of an intelligent vehicle, presenting the control system modules allowing the vehicle to navigate autonomously. Our research group has been developed works on autonomous navigation and driver assistance systems, using CaRINA I platform to experiments and validation. Our platform includes mechanical vehicle adaptations and the development of an embedded software architecture, and its practical implementation. This paper addresses in details the sensing and acting infrastructure. Several experimental tests have been carried out to evaluate both platform and proposed algorithms.**

***Index Terms*—Autonomous vehicle, driving assistance, urban environments, robot platform and software architecture.**

I. Introduction

Human driving errors are a major cause of car accidents on roads. These mistakes are caused by a series of in-car distractions, such as using mobile phones, eating while driving, or more seriously faults like drunk driving or abuse of high speeds. People often get injured or even die due to road traffic collisions. Based on use of sensors and actuators to detect and avoid dangerous situations, autonomous vehicles could provide safer conditions in roads. They could also improve the efficiency with freight transportation and traffic flow in large cities, and also to provide transportation to physically handicapped or visually impaired people.

Researches in autonomous vehicles have achieved significant results over the last years. Competitions, like the DARPA Grand [1] and Urban [2] Challenges and ELROB [3] have been pushing the state of the art in autonomous vehicle research area. In these competitions, some research groups stood out due to the fact that they have developed robotic platforms able to behave like as a human conducted car in several scenarios and conditions.

On this way, a robotic platform which can operate on urban environment and highways is desired by research groups that work with topics related to autonomous vehicles. This aspiration is easily explained by the many possible applications of this platform, and also by the necessity to carry out experiments on real situations in order to validate new intelligent robotic techniques and algorithms. This article aims to present details about the platform developed by LRM Lab. named CaRINA I. Also, we describe a brief overview of works performed by our team that have used this platform to conduct experiments of intelligent vehicle navigation. This paper is organized as follow. The next section describes the structure of hardware and software of the CaRINA I vehicular robotic platform. The Section III presents and summarizes previous works that our lab has implemented in the last two years, all of which are related with several subtopics of autonomous vehicles research, like obstacle avoidance, road recognition, path planning and driving assistance. At section IV the ongoing and future works is addressed, where we introduce a newer robotic platform under development, beyond other ongoing works like automatic parking, planning and vehicle control. Our final remarks are presented in the sequence in the last Section.

Fig. 1. The vehicular robotic platform called CaRINA I

II. Vehicle and System

In this section we describe the main characteristics of the robotic platform CaRINA I, as their hardware resources involved in the processes of perception, action and control. Aspects of software are also presented, as the system architecture and the development frameworks.

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Fig. 2. CaRINA I steering system. In details: (1) motor, (2) coupling system pulley, (3) steering system component, (4) digital encoder, (5) coupling detection switch, (6) coupling handspike, (7) RoboteQ motor controller and (8) limit switches.

A. Hardware

In order to serve as a platform for research in autonomous vehicles, in August 2010 the Mobile Robotics Lab - LRM - acquired a small electric utility vehicle model, Carryall 232 manufactured by the company Clubcar [4]. This vehicle choice was determined by a set of factors like behavior similar to a passenger car in terms of kinematic and dynamic aspects, easiness to carry out the mechanical modifications to turn it into a robotic platform, and greater flexibility and security in performing experimental tests - given the reduced size and weight. Furthermore, we can highlight the low environmental impact due to electric propulsion.

Initially mechanical and electronic vehicle changes were made to allow computational control of the steering wheel, acceleration and braking systems. All these changes also intended to preserve the original driving and handling vehicle characteristics.

The steering system (Fig.2) comprises a Bosch DC motor that connects with the steering wheel through a coupling mechanism consisting of pulleys and belts. A lever allows that steering system can operate in manual mode or pulled by the engine. This set includes an encoder HEDS 5700 Series Hewlett Packard 512 ppr (pulses per revolution) [5], which guarantee the feedback to the control system. Switches fitted in the track rod sends signals when the system reaches the end of the course of steering, allowing the controller to detect the limit and stop the engine. The motor rotation direction control, the determination of the actual angular position of the steering wheel (obtained from the readings of the signals from the encoder), and the limit switch stroke, are performed by a RoboteQ controller AX2850 [6] that can communicate with the main computer using a Serial/USB port.

The vehicle speed control is determined by a system designed by the car manufacturer that maps the throttle pedal position, represented by a variation in voltage, into necessary controls to car electric motor. Some characteristics of this controller took us to consecutive failed attempts to generate this signal artificially. The best result was obtained using an analog potentiometer equivalent to the same mapping of the native system, but which was electronically isolated from the entire car system. Thus, we constructed an electromechanical device that uses Arduino Duemillenove kit and servo mechanism to adjust the position of the potentiometer responsible for varying the voltage supplied to the controller (Fig. 3).

Fig. 3. Throttle controller device. At right, the inside view with highlights to Arduino and mechanical coupling between servo motor and potentiometer.

For the braking system a linear actuator from LINAK LA12 200N [7] was mechanically coupled in parallel with the brake system of the vehicle. When triggered, the actuator tension part of the system, reproducing the behavior of the driver by pressing the brake pedal. A second RoboteQ channel is used to control this actuator.

The platform includes supporting bases and structures built especially for the installation of lasers, cameras and other sensors. In the CaRINA I front it has two Sick LMS 291 lasers [8], one mounted aligned in parallel to the ground and the other pitch down, pointing at the region just ahead the vehicle. A bracket installed on the roof of the vehicle allows the installation of different types of video cameras and adjusting its position, allowing the possibility of using monocular or stereo cameras, as the ones from Videre [9]. At the rear, two lasers houses supports Hokuyos UTM-30LX [10] which beams cover both side areas on the rear of the vehicle (Fig. 4). Additional sensors supplement the available resources of perception, namely: a GPS receiver and inertial drive (IMU) model MTI-G XSens [11], a Revolution GS True North compass [12] and another series HEDS 5700 encoder mounted on the ground wheel, responsible for providing data used to compute the odometry.

B. Frameworks

Widespread used by the scientific community, the software platform Player/Stage consists of a development framework that offers several features like client/server model, that allows the user to run applications remotely over a TCP/IP network, simulated environments, libraries that encode algorithms of localization, mapping and control.

In order to use the Player/Stage platform, a plugin for the CaRINA I was specially developed to serve as driver and allow receiving commands from the framework which are properly mapped to the corresponding command controls for

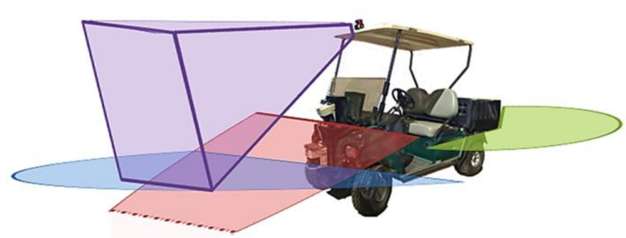

Fig. 4. CaRINA's perception planes and sensing areas: horizontal laser plane (blue), pitch down laser plane (red), rear and lateral areas by hokuyo (green) and camera view (purple).

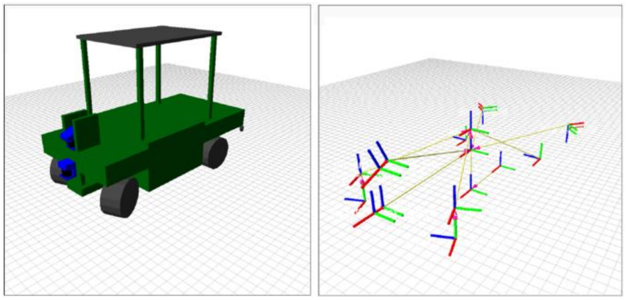

Fig. 5. CaRINA's model. The 3D vehicle model view and his coordinate frames system.

vehicle control system. This module also incorporates the vehicle kinematic features according to Ackerman's model, providing correspondence and coherence among odometer and speed data provided by the framework and what is being done by the vehicle. It is noteworthy that even this approach does not eliminate the typical problems of imprecision in estimating the pose of the vehicle based solely on data from odometry.

Recognizing the Player software limitations in face of the computational demand to develop an autonomous vehicle system, we decided work with another software base besides Player, named ROS – Robotic Operating System. Although called operating system, this platform is a distributed and service-oriented middleware developed by Willow Garage in conjunction with the international community. One of our aims to adopt this system is that it can allows us to design the software components in modular and interchangeable manner, as well as, allowing our software components to be executed in a distributed system, balancing the computational requirements at different processing elements and PCs.

C. *Modeling and Simulation*

Although important, the realization of practical experiments to validate the algorithms and techniques under development can be a dangerous activity if performed without a degree of certainty and reliability considered acceptable. In this sense, simulation tools allow to conduct preliminary tests to evaluate the system response in scenarios very similar to the application domain.

In addition to the mathematical modeling of kinematic aspects of the vehicle, were also created 2D and 3D models that incorporate the geometrical and physical CaRINA I characteristics, allowing more realistic simulations with Stage and Gazebo simulators, which are both compatible with the Player and ROS (Fig. 5).

D. *System architecture*

The Autonomous Vehicle Control System should provide a series of basic and advanced functionalities. Autonomous navigation or even driver assistance (ADAS - Advanced Driver Assistance Systems) while conducting a vehicle into urban environment, requires a system which can recognize some elements like traffic signs, pedestrians and other vehicles. Also, correct localization keeping the vehicle in the road, making safely overtaking maneuvers, as well as respecting what determines the traffic laws [13]. The development of a system with these skills is a complex task, requiring the use of different techniques simultaneously coordinated at a higher level in order to provide consistency and robustness.

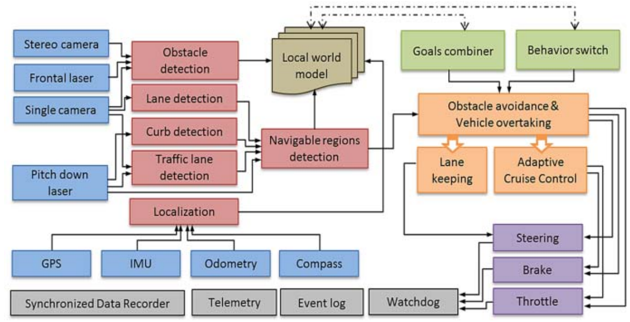

Fig. 6. CaRINA's System Architecture. Modules: Sensing (blue), fusion and feature extraction (red), high level judge (green), behaviors in different levels (orange), actuation drivers (purple) and backward system guard (light gray).

Inspired by [14] [15], we arrived to our reference architecture with hierarchical and hybrid features, as well as, being able to merge functional and behavioral aspects. In Figure 6 we present a schematic diagram of this architecture, with details of some of its main modules and interconnections. Encapsulating the device drivers and their communication channels, specific modules operate in the interface of software systems, allowing for the physical command of steering, acceleration and braking of the vehicle. Interacting directly with them, the control subsystem is responsible for accommodating the reactive and deliberative behaviors governing the vehicle within its local perception.

Modules of perception are responsible for acquiring and providing sensory data into richer forms of representation, and also in structured form, allowing the simple, fast and reliable identification of relevant aspects in the car scenario (urban environment). The combination of information takes place by merging data on a subsequent layer or level which is responsible for feature extraction and detection of structural elements of the environment. Tasks such as obstacle detection, localization and identification of navigable regions are performed by modules at this level, the results being stored in a representative model of the local surrounding environment. Finally, a subsystem backup is needed to maintain critical aspects of security, operations and records of decisions taken by the system (log), remote monitoring and storage of raw data allowing more thorough analysis, post-processing or even the creation of databases for simulation. It is noteworthy that some of these elements, especially the higher level, are still under development.

III. Recent Research Efforts under LRM

In this research area, the LRM try to cover the main aspects related to autonomous vehicles in urban environments. Our main objectives include: develop driver assistance systems, autonomous control and navigation, machine learning and vision systems approaches applied to intelligent vechicles, and convoy control and management.

Both the development of robotic platform and the different investigations of these themes were conducted in the last two years at the LRM Lab. Several experiments were carry out using CaRINA I, in order to validate the proposed architecture and implementations, and some of the results are shown below. Although the description below of each approach and obtained results is relatively short, a detailed description of the techniques, algorithms, and results, can be found in the references presented together with this text.

A. Obstacle detection and Driving assistance

For both autonomous navigation and driver assistance system, precise and robust obstacle detection is fundamental, generating alerts and guaranteeing a safe navigation.

Among the desired features for a system that helps the driver to know about obstacles are low rates of false positive (avoid undesired warnings and situation judgment mistakes). In other words, it is necessary to differentiate which of detected elements can really be dangerous, related to the vehicle estimated trajectory.

In a first implementation of an ADAS approach (driver assistance), the sensors information fusion from 2D laser scans (single laser beam plane), GPS receiver, and compass, through an intelligent adaptive algorithm, combines these data to create an attention region. The system differentiates potential harmful objects of real dangerous obstacles near to the vehicle [16] from normal obstacles that are located around the vehicle but outside of the planned trajectory. As expected, in the tests conducted using real situations and sensors acquired data, demonstrated that proposed approach allowed a significantly reduction in the number of false alarms of possible collisions.

The obstacle avoidance was also addressed in [17], but instead of using a laser based sensor, it was adopted a stereo camera based approach. Initially, a stereo image pair was processed by a semi-global stereo method in order to obtain the disparity map (depth map). This map is then converted into a 3D point cloud representation based on the extrinsic parameters of the stereo camera. Understanding that, the major points present in the cloud refer to flat regions (as the ground), we used a RANSAC paradigm to extract a plane model from the point cloud. This plane also tends to refer to a navigable region (flat), then the algorithm checks the distance of each other point to the estimated plane and classify them as non-obstacles (near the plane) or obstacles (far away from the plane). Although this technique has been used by many works as mentioned in [18] [19] it is subjected to some limitations, for example (i) plane is not appropriated to model curved terrains; (ii) there is no guarantee that the estimated plane refers to the navigable region.

Due to the known limitations of plane based technique, another method for better obstacle detection was sought. Proposed by [20], the "cone based" method analyzes the points' dispersion according to a conical projection. Limited upper and below by a threshold, any giving point that belong to own projection is considered compatible. The algorithm premise is, if two points are compatibles they belong to an obstacle. This method yields great results however its main limitation is the computational costs. To tackle this issue a GPU implementation is under developing and the preliminary tests demonstrated that the method can achieve a computing time of 18 milliseconds on average. These results are not yet published, but they are very encouraging.

B. Terrain reconstruction and road detection

The road recognition ability, also known as "lane detection", "road detection" and "road following", is one of the very desirable skills adopted to improve autonomous vehicles systems. Using a sweeping 2D laser scanner (planar scan) mounted in a pitch down view is possible to reconstruct the terrain surface ahead the vehicle and identify the road by features extraction and classification from raw data. For each obtained scan, resultant points sets represent the intersection between laser and terrain planes (slices). Knowing the laser angle and vehicle pose along the trajectory, is possible to build a tridimensional representation of terrain shape by integrating over time the successive points sets.

In [21] [22] an approach based on Artificial Neural Networks and Support Vector Machines was used to extract features from topographic outlines and classify them into navigable (almost flat) and non-navigable regions (non-flat/with obstacles). A small size mobile robot was used in these experiments. Adapting this idea to vehicle navigation into urban context, our approach adopted a morphological outline analysis of the resulting point set to identify the curbs position and its distances from the vehicle. This information was used by the navigation controller to keep the vehicle in the lane with a safety and constant distance to the curbs. The Figure 7 presents an example of the road classification into navigable (center) and non-navigable (border) areas.

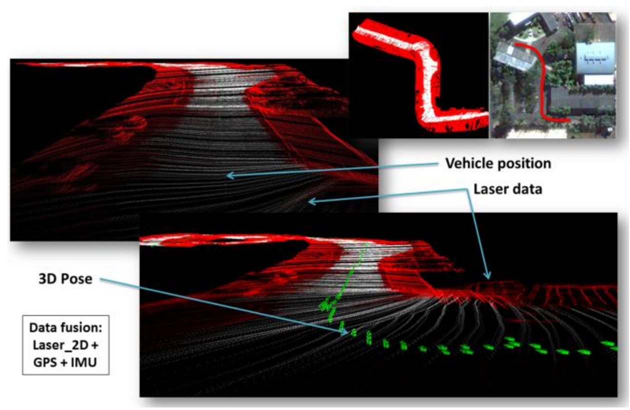

Fig. 7. Laser Data: Detecting navigable (white zone) and non-navigable (red zone) regions in the laser scan of a road. The dots (green) represent the vehicle pose during navigation and data capture, based on GPS and IMU.

On the other hand, visual based recognition systems have been developed by many research groups since the early 1980s, such as [23] [24] [25]. One of the most representative works in this area is the NAVLAB project [25] with ALVINN system [26]. According to [27], this approach only works on straight or slightly curved roads. Also, according to [27], the major problem of ALVINN is the lack of ability to learn features which would allow the system to drive on road types other than that on which it was trained. Some other approaches like [28] make suppositions to adapt the system and solve these problems. However, these suppositions have no guaranties to work well in real urban environments.

Some previous works presented by our group, proposes a visual road detection system that uses multiple ANNs (Artificial Neural Networks) in order to improve the robustness. A detailed description of these works can be found in [29] [30]. A set of multiple ANNs learns to recognize colors and textures from sub-images instead of using all the road appearance like ALVINN does. In our system, each ANN receives different image features as input. Features like averages, entropy, energy and variance from differrents color channels (RGB, HSV, YUV), obtained from sub-images are presented as inputs to the ANNs. In the final step of the algorithm, we combine a set of ANNs outputs to generate one single classification for each sub-image. Other important detail about this classification system is that it provides a confidence factor for each sub-image classification that can be used by the control system (confidence in the region classification as navigable/road or non-navigable/obstacle). Unlike [28], our system does not need to be retrained all the time because the generalization capacity of our system is better than theirs. Therefore, our system does not require making assumptions about the location of the road in the image. A more recent work [31] incorporates a method that estimates the height of the horizon line in image in order to improve the classification of images and make the system faster.

Another approach developed by our group is use of a stereo vision system in order to improve the classification of the machine learning techniques. This system has been used in the task of road recognition, once we can obtain depth information from the acquired stereo image, separating the ground from the obstacles. The main idea of these works consists of incorporating the disparity information as input of Machine Learning techniques. More details about this can be founded in [32] and [33]. The use of the disparity map information contributed in decreasing the false positives, i.e., when the camera "sees" an obstacle the ANN classifies this region of image as "non-road" with a high degree of confidence.

C. *Automatic learning*

One of our research purposes as a group is to develop an autonomous navigation system capable of learning from the human driver experience of vehicle conduction. Several works are under development to tackle with this problem.

Using the vision system, mentioned in subsection B above, to identify the navigable area [29], the proposed approach applied a template matching algorithm [34] on the image, evaluating the degree of matching of binary masks on the classified images. We evaluated five masks, which correspond to the following maneuvers: go forward (straight line), turn left/right (soft and hard curve to left/right). In the first experiments, CaRINA I was able to avoid the road border, keeping the vehicle on the road/lane and performing curves, along a path of approximately 300m [35]. The same algorithm has been improved and again validated, now in urban environments on the presence of obstacles. In this second group of experiments CaRINA I was able to avoid people and other vehicles; keeping it in the road [36].

Other more advanced work, integrated the navigation algorithms with information obtained from the GPS and digital compass, enabling the autonomous navigation to follow a predetermined path, and at the same time, respecting the limits of the navigable area and avoiding obstacles. Combining the approaches presented in [35] and [37], information of GPS, compass and of the image processing were used together as inputs of an ANN whose outputs determined the controls of steering and speed of the vehicle. Several tests were performed in small trajectories [38], and after some improvements, the vehicle performed a path of approximately 1.1 km using uniquely as reference a total of 6 (six) GPS points defining the path. The results have shown that CaRINA I was able to identify and stay in the navigable area, besides the crossing of roundabouts, which was done successfully. Even when a virtual straight path, defined by the alignment between the vehicle local GPS position and the destination position, passed through and over sidewalks, flower beds and grass fields, in all those situations CaRINA I followed the perfect trajectory. All over the path the vehicle remained on the road and reached the destination without bumping or scraping the sidewalk border (border of the road). A more complete analysis of the integration of these vision algorithms and autonomous navigation methods using supervised learning was described in [39].

IV. Ongoing and Future works

After the maturity gained by our research group along of all these projects, including the aspects that adapted a commercial platform (Carryall Electric Vehicle) into a robotic platform (CaRINA I), we started the mechanical changes in a commercial vehicle of FIAT (Palio Weekend Adventure) in the end of 2011. This platform was called CARINA II. This new platform will explore more advanced techniques for autonomous navigation in urban environments, in order to achieve a fully autonomous commercial robotic platform.

A new work using autonomous navigation and learning by imitation now tries, through a second ANN, to learn and relate the visual perception with the controls of steering and speed of a human driver. Preliminary tests demonstrate the ability of the ANN to replicate the driver behavior on the same situations, but not all the maneuvers were performed properly [40]. A new methodology for capturing information and pre-processing the data is under development.

The group has worked in the integration of the existing elements described previously to operate as a single system. Interfaces are standardized to make them compatible with the both CaRINA platforms. Other initiatives related to automatic parking, planning and control of trajectories are topics covered in Master dissertations and Doctoral thesis within our research group.

V. Final remarks

This paper have described the CaRINA I platform design and implementation, in terms of hardware and software. This research project, supported by the INCT-SEC and developed at LRM Lab., was divided into different development stages, ranging from the design of the electromechanical aspects of the vehicle, the vehicle control system architecture, the development of software components and modules, the adoption of simulation tools and robotics supporting software, and finally the proposed implementations, experiments and results .

The CaRINA I project represents one of the most important Brazilian initiatives in this domain of research, among other few initiatives in this country that also develop autonomous and/or automated vehicles (e.g. CADU-UFMG, Drive4U-UNIFEI, VERO-CTI/CenPRA, and Project SENA-USP EESC/ICMC). The CaRINA I was the first completely autonomous vehicle developed at USP, which also demonstrated in practical experiments several intelligent behaviors based on computer vision, sensor fusion and GPS based navigation.

A new platform, CaRINA II, is under development, and the know-how obtained during the development of this first autonomous platform is now being transferred to this new project.

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