A Real-Time Navigation Architecture for Automated Vehicles in Urban Environments

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***Abstract*— This paper presents a novel navigation architecture for automated car-like vehicles in urban environments. Motion safety is a critical issue in such environments given that they are partially known and highly dynamic with moving objects (other vehicles, pedestrians...). The main feature of the navigation architecture proposed is its ability to make *safe* motion decision *in real-time*, thus taking into account the harsh constraints imposed by the type of environments considered. The architecture is based upon an efficient publish/subscribe-based middleware system that allows modularity in design and the easy integration of the key functional components required for autonomous navigation: perception, localisation, mapping, real-time motion planning and motion tracking. After an overall presentation of the architecture and its main modules, the paper focuses on the "motion" components of the architecture. Experimental results carried out on both a simulation platform and a Cycab vehicle in a parking environment are presented.**

I. Introduction

Intelligent Transport Systems (ITS) have been considered in the past ten years or so as a possible response to a number of problems related to the increased usage of private vehicles worldwide, namely pollution, congestion and safety problems [1]. One of the long-term goals is to reduce the use of the private car in downtown areas by offering novel modern and convenient public transportation systems. The Cybercar concept is a vivid example of such innovative transport systems. Cybercars are road vehicles with fully automated driving capabilities. A fleet of such vehicles would form a managed transportation system, for passengers or goods, on a network of roads with on-demand and door-to-door capability (http://www.cybercars.org). This concept emerged in Europe in the early 1990's and was demonstrated for the first time in the Netherlands in December 1997 for passenger transport at Schipol airport. As of today, Cybercars operate on dedicated and protected road-networks only. The next step is to take them to open environments featuring other vehicles, pedestrians, *etc.*

Autonomous navigation requires to solve a number of challenging problems in domains as different as perception, localization, environment modelling, reasoning and decision-making, control, *etc.* The problem of designing and integrating these functionalities within a single navigation architecture is of a fundamental importance. Since Shakey's pioneering attempts at navigating around autonomously in the late sixties [2], the number and variety of autonomous navigation architectures that have been proposed is large (see [3]). From the motion determination perspective, these navigation architectures can be broadly classified into *deliberative* (*aka motion planning-based*) versus *reactive* approaches: deliberative approaches aim at computing a complete motion all the way to the goal using motion planning techniques, whereas reactive approaches determine the motion to be executed during the next time-step only. Deliberative approaches have to solve a motion planning problem [4]. They require a model of the environment as complete as possible and their intrinsic complexity is such that it may preclude their application in dynamic environments: indeed, the vehicle has a limited time only to determine its future course of action (by standing still for too long, it might be collided by one of the moving objects). Reactive approaches on the other hand can operate on-line using local sensor information: they can be used in any kind of environment whether unknown, changing or dynamic. This accounts for the large number of reactive approaches that have been developed over the years, *eg* [5], [6], [7], [8], *etc.* Most of today's reactive approaches however face a major challenge: as shown in [9], motion safety in dynamic environments is not guaranteed (in the sense that the vehicle may end up in a situation where a collision inevitably occurs at some point in the future).

The primary contribution of this paper is a motion planning module that takes into account these two constraints, namely the *real-time* and *safety* constraints. It is achieved thanks to the two concepts of Partial Motion Planning (PMP) [10] and Inevitable Collision States (ICS) [11]. PMP is a planning scheme that take into account the real-time constraint explicitly. PMP has an anytime flavor: when the time available is over, PMP is interrupted and it returns a partial motion, *ie* a motion that may not necessarily reach the goal. This partial motion is then passed along to the navigation system of the vehicle for execution. Of course, since only a partial motion is computed, it is necessary to iterate the partial motion planning process until the goal is reached. Like reactive decision scheme, PMP faces the safety issue. ICS are called upon to address this issue. An ICS is a state for which, no matter what the future trajectory followed by the vehicle is, a collision with an object eventually occurs. For obvious safety reasons, a vehicle should never ever end up in an ICS. By computing *ICS-free partial motion* at each time-step, the vehicle's safety *can be guaranteed* in real-time.

The secondary contribution of this paper is a presentation of the navigation architecture hosting the PMP-ICS motion planner. It is based upon an efficient publish/subscribe-based middleware system named DDX [12] that allows modularity in design and the easy integration of the key functional components required for autonomous navigation: perception,

TABLE I

DDX STORE: WHO IS USING WHAT?

Module	Input/Output Data
Localization	Input: CycabPose, CycabState, GIS, Landmarks Output: CycabPose
World Modelling	Input: GIS, Moving Objects Output: Future Model
Motion Planning	Input: Future Model Output: Trajectory
Motion Tracking	Input: CycabPose, Trajectory Output: CycabCommand

localization, world modelling, motion planning and motion tracking.

The paper is organised as follows: first, an overall description of the navigation architecture is given in section II. The three layers of this architecture are respectively detailed in sections III, IV and V. Experimental results are finally presented in section VI.

II. NAVIGATION ARCHITECTURE OVERVIEW

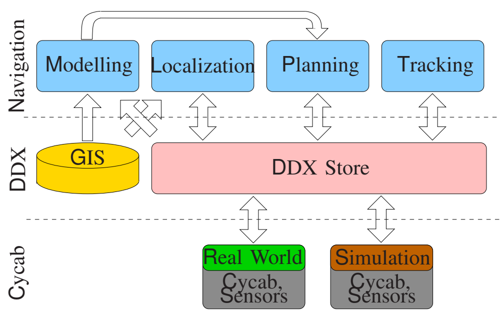


Fig. 1. Functional view of the navigation architecture.

The architecture presented in this paper is a DDX-based real-time modular architecture. DDX is a publish/subscribe-based middleware [12] that is used to provide the navigation modules with an abstract view of the Cycab, its sensors and its environment. Fig. 1 depicts the overall architecture. Below the DDX layer is the Cycab layer: it features the Cycab, its sensors and the environment either in simulation or for real. Above the DDX layer is the Navigation layer: it features the different key modules required for autonomous navigation: localization, world modelling, motion planning and motion tracking (these modules are detailed in section V). To complete the architecture, a Geographic Information System (GIS) is used to provide static information about the environment (road geometry and topology, traffic signs and traffic rules...), as opposed to the dynamic information about the environment (other vehicles, pedestrians...) which is computed by the Cycab layer through sensor-data processing (or directly by the simulator). The following sections describe the DDX, the Cycab and the Navigation layers respectively.

III. DDX LAYER

DDX provides an efficient communication mechanism to allow multiple processes to share data. It is implemented as a *store*, *ie* a block of shared memory (possibly distributed over several computers), that is used to store shared information. The *Catalog* function is used to ensure the coherence of the information contained in the different stores (using the UDP/IP communication protocol). As far as the navigation architecture proposed is concerned, the data contained in the DDX store comprises four main data structures concerning either the Cycab or its environment:

- **Cycab:** information concerning the Cycab:
  - *CycabState*: encoder values, wheel velocities....
  - *CycabCommand*: actuator commands (speed, steering angle).
  - *CycabPose*: position and orientation of the Cycab.
- **Landmarks:** position of the observed landmarks, *ie* the salient features of the environment used for absolute localization (see section V-B).
- **Trajectory:** nominal trajectory that is to be executed by the vehicle (see section V-C). It is a sequence of (state, time) couples.
- **Moving objects:** list of the moving objects observed in the environment. Each moving object is characterized by it shape, position, orientation and velocity.

Table I summarizes how these data structures are used by the different navigation modules. The GIS data used by Localization is the list of the landmarks' position. World Modelling on the other hand gets the road geometry from GIS. Future Model is a description of the current state of the environment (fixed and moving objects) plus a prediction of the future motion of the moving objects (see section V-A).

IV. CYCAB LAYER

A. Cycab Vehicle

The Cycab vehicle is a lightweight urban electric vehicle which is specifically designed for downtown areas (Fig.5). It can be driven using a joystick (manual mode) but is also equipped to be fully computer-controlled (automatic mode). Its maximum speed is 30 km/h and it can accommodate two people along with their luggage. It is used by the different Inria research centers as an experimental platform for research on Intelligent Transport Systems. Its mechanical structure is similar to that of a small golf cart. It integrates four motor wheels and a motorized mechanical jack for steering. Micro-controllers are used to control of the motor-wheels and the steering mechanism. An embedded PC under Linux RTAI is used for the overall control of the vehicle. Two CAN (Controller Area Network) buses are used for communication between the different hardware components of the vehicle. It can be equipped with various sensors such as GPS, IMU, video cameras and range sensors (more details at http://www-lara.inria.fr/cycaba).

B. Cycab Simulator

The Cycab Simulator has been designed to facilitate the design and test of the algorithms for automated driving in dynamic urban environments that will be implemented on the real Cycab. It is based upon the MGengine simulation engine (http://mgengine.sourceforge.net) and permits the simulation of the Cycab vehicle, its sensors and its environment. Figs. 7(a) and 8(a) depict snapshot of the simulator GUI (more details at http://cycabtk.gforge.inria.fr).

V. Navigation Layer

This section presents the main modules used for autonomous navigation. There are four of them: *World Modelling* and *Localization* that deals with building a model of the vehicle's environment and localizing the vehicle inside this model. *Motion Planning* and *Motion Tracking* respectively deals with computing and executing a trajectory. These modules are described in the next four sections with a particular emphasis on the "motion" modules.

A. World modelling

The primary purpose of the World Modelling module is to build a model of the environment of the vehicle that can be used for autonomous navigation purposes. Road-like environments feature both *fixed objects* (such as building) and *moving objects* (such as other vehicles and pedestrians) and the World Model must represent them both. In the road-driving context, static information about the environment can be obtained from a GIS and it is up to the on-board sensors to provide the dynamic information. In addition to that, the Motion Planning module requires additional information about the *topology of the road network* and a *model of the future*, *ie* information about the future behaviour of the moving objects (see section V-C). The next three sections respectively overview how are obtained the static and dynamic information and the model of the future.

1) Static Information:

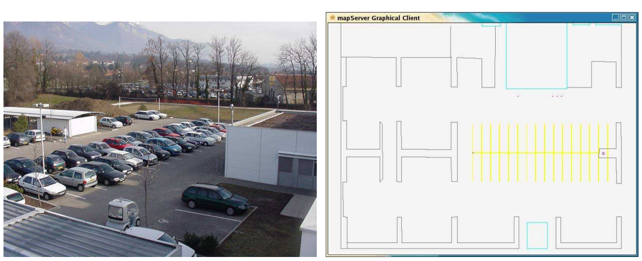


Fig. 2. View of the parking lot (left) and the corresponding map (right).

Static information about the environment, *eg* limits of the roadway, geometry of the obstacles, *etc.* are assumed to be a priori known and made available in a Geographic Information System (GIS). For the purpose of navigation in urban environments, a two-dimensional map of the environment (*ie* a set of polygonal obstacles) suffices (Fig. 2). In addition to this two-dimensional map, the GIS contains information about the landmarks of the environment that are used for localization purposes (see section V-B). The structure of the roadway is also included in the GIS: it is represented as oriented lanes connected together in a network. This structure is exploited by the Motion Planning module to determine the route that is to be followed in order to reach a given goal (see section V-C).

2) Dynamic Information:

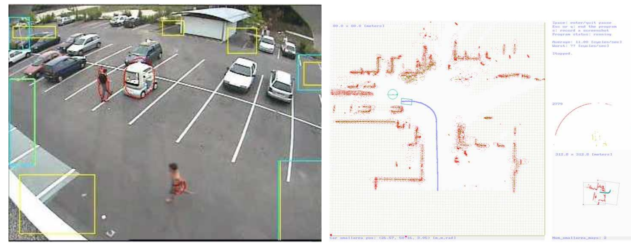


Fig. 3. Detecting and tracking moving objects using an off-board video camera (left) and an on-board laser range sensor (right).

The dynamic information includes all the environmental objects that are not represented in the GIS. It concerns the moving objects of the environment mostly, *eg* other vehicles, pedestrians, *etc.* It is up to the different exteroceptive sensors to detect these moving objects on-line. The Motion Planning module requires not only the position and shape of these moving objects but also information about their dynamics (linear and/or angular velocity, acceleration, *etc.*) and whatever information that can be used to predict their future behaviour (if it is signaling a turn for instance). For the time being, only the linear velocity information is determined. In the architecture proposed, it is assumed that the information about the moving objects is a direct output of a sensor-processing step corresponding to the different sensors used. In other words, the detection and tracking of the moving objects is performed in the Cycab layer, not the Navigation layer (Fig. 1). Detecting and tracking moving objects is one of the key challenge in perception. A wide range of techniques are now available for different sensors, *eg* video cameras, laser or radar, (see [13]). Experiments have been carried out using video cameras and laser range sensor and the tracking techniques presented in [14] and [10] (Fig. 3).

3) Future Prediction:

Fig. 4. Predicting the future motion of a moving object in a parking lot.

Decision-making in general and motion planning in particular involves a certain degree of reasoning about the future: you decide now what you will do next: knowledge about the future is therefore necessary. When it comes to motion planning, long-term knowledge about the future motion of the moving objects is required. This knowledge is usually not available a priori and one has to resort to prediction. In the architecture proposed, motion prediction relies upon the assumption that pedestrians and vehicles do not move randomly but follow typical "motion patterns" which may be learned and then used in a prediction phase. Fig. 4 illustrates the motion prediction process: the left image depicts the networks of motion patterns that have been learned from a set of observed moving object's motions. The center image shows a moving object being tracked by the vision system. The right image plots the different goals that this moving object is likely to reach with their associated probabilities. The trajectory leading to these goals is also computed. The reader is referred to [15] for more details.

B. Localization

The primary purpose of the localization module is to determine where the vehicle is in its environment (position and orientation). The Localization module combines odometric relative positioning and landmark-based absolute positioning in order to achieve the required robustness and accuracy of localization. Odometric localization is achieved by using encoder data (wheels, steering angle) and standard Extended Kalman Filters (EKF). Landmark-based localization is achieved by matching observed landmarks, *ie* specific features of the environment, with a priori known information about the landmarks present in the environment (obtained from the GIS). A laser range-sensor is used to detect the artificial landmarks located in the surroundings of the vehicle. The vehicle's pose is calculated by triangulation thanks to the range-bearing data associated to the observed landmarks and their GIS coordinates. The fusion of odometric with landmark-based localization results is also made by means of an EKF. The reader is referred to [16] for more details.

C. Motion Planning

The Motion Planning module is the key component of the solution proposed for motion autonomy in dynamic environments. Its purpose is to compute the trajectory that is to be executed by the vehicle in order to reach its goal. As mentioned in the section I, the Motion Planning module takes into account the two constraints imposed by dynamic environments, namely the *real-time* and *safety* constraints. It is achieved thanks to the two concept of Partial Motion Planning (PMP) [10] and Inevitable Collision States (ICS) [11]. The Motion Planning module takes as input the model of the future provided by the World Modelling module, computes a trajectory and places it into the DDX store where it is available for the Motion Tracking module. The next two sections respectively describe PMP and ICS.

1) Model of the Vehicle:

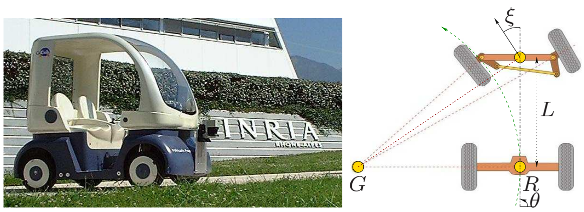


Fig. 5. The Cycab vehicle and its kinematics.

Let $\mathcal{A}$ denote the Cycab vehicle. A *state* of $\mathcal{A}$ is defined as a 5-tuple (x, y, θ, v, ξ) where (x, y) are the coordinates of the middle point R of the rear axle, θ is the main orientation of $\mathcal{A}$, v is the linear velocity of the rear wheel, and ξ is the orientation of the front wheels (Fig. 5). A *control* of $\mathcal{A}$ is defined by the couple (α, γ) where α is the rear wheel linear acceleration. and γ the steering velocity. The motion of $\mathcal{A}$ is governed by the following motion equation:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{v} \\ \dot{\xi} \end{bmatrix} = \begin{bmatrix} v\cos\theta \\ v\sin\theta \\ \frac{\tan\xi v}{L} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \alpha + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \gamma \tag{1}$$

with $\alpha \in [\alpha_{min}, \alpha_{max}]$ (acceleration bounds), $\gamma \in [\gamma_{min}, \gamma_{max}]$ (steering velocity bounds), and $|\xi| \leq \xi_{max}$ (steering angle bounds). L is the wheelbase of $\mathcal{A}$.

2) Partial Motion Planning:

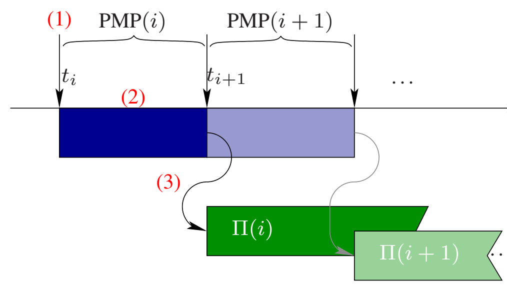


Fig. 6. Partial Motion Planning iterative cycle.

When placed in a dynamic environment, a vehicle cannot stand still since it might be collided by one of the moving objects. In a situation like this, a *real-time constraint* is imposed to the vehicle: it has a limited time only to determine its future course of action. The time available is a function of what is called the *dynamicity* of the environment which is directly related to the dynamics of both the moving objects and the robotic system.

As mentioned earlier, *Partial Motion Planning* (PMP) is a planning scheme that takes into account the real-time constraint explicitly: when the time available is over, PMP is interrupted and it returns a partial motion, *ie* a motion that may not necessarily reach the goal. Of course, since only a partial motion is computed, it is necessary to iterate the partial motion planning process until the goal is reached. The iterative nature of PMP is doubly required since the model of the future is based upon predictions whose validity duration is limited in most cases. An iterative planning scheme permits to take into account the unexpected changes of the environment by updating the predictions at a given frequency (which is also determined by the environment dynamicity). Fig. 6 depicts the PMP iterative cycle. Let us focus on the planning iteration starting at time ti, it comprises three steps:

(1) An updated model of the future is acquired (provided by the World Modelling module).
(2) The state-time space of $\mathcal{A}$ is searched using an incremental exploration method that builds a tree rooted at the state $s(t_{i+1})$ with $t_{i+1} = t_i + \delta_p$ where δ_p is the planning time available.

(3) At time t_{i+1}, the current cycle is over, the best partial trajectory $\Pi(i)$ of the tree is selected according to a given criterion (safety, length, *etc.*). It is discretized and placed into the DDX store.

PMP cycles until the last state of the planned trajectory reaches a neighbourhood of the goal state. An incremental search method is used to explore the state-space. It is based upon the Rapidly-Exploring Random Tree (RRT) technique [4] that incrementally expands a tree rooted at the start state. This method being incremental in nature, it can interrupted at any time. Classically, RRT computes collision-free trajectories. In the approach proposed, the usual geometric collision-checker is replaced by an Inevitable Collision State-checker [17] that ensures that $\mathcal{A}$ will never end up in a situation eventually yielding a collision later in the future.

D. Motion Tracking

Motion tracking control deals with the execution of the planned trajectory. The Motion Tracking module is essentially a feedback controller that seeks to minimize the error between the current state of the vehicle and the desired state. Both states are obtained from the DDX store, they are respectively computed by the Localization and the Motion Planning modules.

For tracking purposes, a motion model simpler than (1) is used instead. A *state* is now defined as a 3-tuple (x, y, θ). and a *control* by the couple (v, ξ). The motion of $\mathcal{A}$ is thus governed by the following motion equation:

$$\begin{cases} \dot{x} = v\cos(\theta) \\ \dot{y} = v\sin(\theta) \\ \dot{\theta} = v\frac{\tan\xi}{L} \end{cases} \tag{2}$$

The tracking problem is considered as tracking a moving reference frame which is moving along a given trajectory. The trajectory tracking error $e = (e_x, e_y)$ is the difference between the current position and the desired position of the robot. The error in the orientation between the current and the reference frames is e_θ. A linearized 5th-order dynamic model is used for the controller design [18]. This model is decoupled into a longitudinal model and a lateral model. Let (v^*, ξ^*) denote the velocity and steering angle of the reference frame, the expected velocity v_c and steering angle ξ_c are obtained as:

$$v_c = v^* - k_v \begin{bmatrix} e_x \\ v - v^* \end{bmatrix}; \xi_c = \xi^* - k_\xi \begin{bmatrix} e_y \\ e_\theta \\ \xi - \xi^* \end{bmatrix} \tag{3}$$

where $k_v = (k_{v1}, k_{v2})$ and $k_\xi = (k_{\xi 1}, k_{\xi 2}, k_{\xi 3})$. The $k_{vi} (i = 1, 2)$ and $k_{\xi j} (j = 1, 2, 3)$ are positive scalar gains (they will determine the tracking performance).

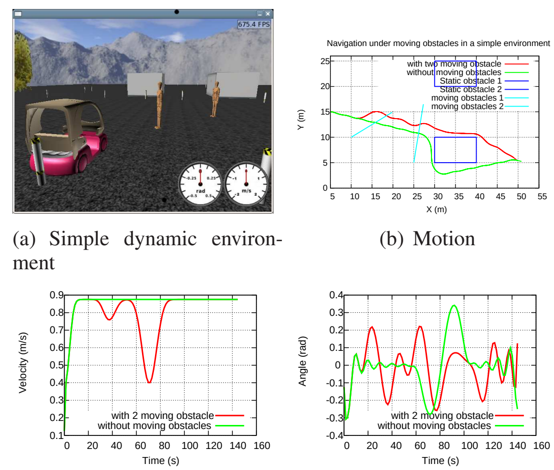
VI. Experiments

The different modules of the navigation architecture are implemented in C++ under Linux. The DDX framework allows the different navigation functionalities/modules to be distributed over different computers. when the real Cycab is used, its embedded core software communicates with the rest of the application through wireless Ethernet. Experiments on autonomous navigation has been carried out in simulation. So far, only the localization and tracking modules have been tested on the real Cycab. Autonomous navigation experiments with the real Cycab are underway.

A. Simulation Results

As mentioned earlier, PMP plays an key role for safe navigation in dynamic environments. Simulations for two different scenarios are first studied to test the real-time planning performance of PMP.

1) Test Environment:



(a) Simple dynamic environment

(b) Motion

(c) Velocity

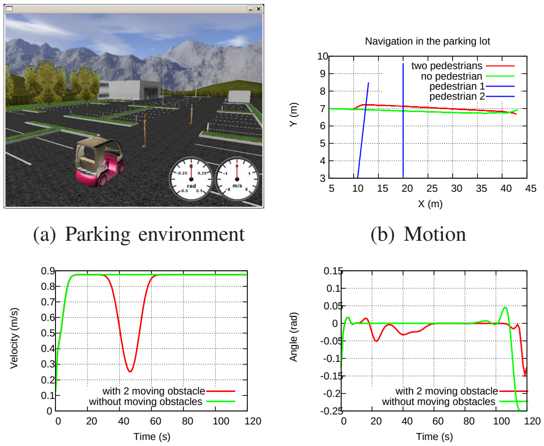
(d) Steering angle

Fig. 7. Experiment in a test environment.

The first experiment is done in a dynamic two-dimensional environment (size $60 \times 30m$), featuring two static rectangular objects and two moving disk objects (Fig. 7(a)). The start and the goal pose of the Cycab are $(5, 15, 0)$ and $(50, 5, 0)$ respectively. The moving objects are programmed to move with a constant velocity (moving upwards). Fig. 7(b) shows the setup of this experiment and the output of the motion planning process. The safe motion planned for the Cycab is the red line passing the two rectangular objects. In comparison, the green line passing below the two rectangular objects is the trajectory obtained when the moving objects are not present. Figs 7(c) and 7(d) depicts the velocity and steering angle profile along both trajectories. The difference between the two trajectories is clearly due to the presence of the moving objects. Notice how the vehicle modify its course (Fig. 7(d)) and slows down twice in order to give way to the moving objects (Fig. 7(c)).

2) Parking Lot of Inria Rhône-Alpes :

The second experiment is done in a two-dimensional model of the parking lot of Inria Rhône-Alpes (Fig. 8(a)). This environment is cluttered with twenty-six fixed objects and two pedestrians. From the motion planning point of view, this environment imposes more collision-avoidance constraints than the first scenario. The starting pose and



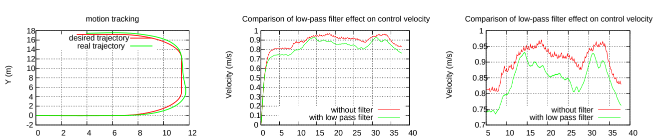
(a) Parking environment (b) Motion

(c) Velocity (d) Steering angle

Fig. 8. Experiment in the parking lot of Inria Rhône-Alpes.

the goal pose of the Cycab is $(5, 7, 0)$ and $(43, 7, 0.1)$ respectively. The pedestrians move upwards on the roadway. Fig. 8(b) shows the setup of this experiment and the output of the motion planning process. It also features the trajectory obtained when the moving objects are not present. Figs 8(c) and 8(d) depicts the velocity and steering angle profile along both trajectories. In this scenario, because of the extra constraint imposed by the fixed objects,, the two trajectories are geometrically close (there is little room for manoeuvring). Most of the differences occur in the velocity profile.

B. Real Experiments



(a) Tracking results (b) Filtered *vs* non-filtered velocity profiles (c) Velocity profiles close-up

Fig. 9. Tracking of a U-shaped trajectory.

Preliminary experiments with the real Cycab vehicle have been done in the parking lot of Inria Rhône-Alpes in order to evaluate the performance of the Motion Tracking module. As per (3), five parameters $(k_{v1}, k_{v2}, k_{\xi1}, k_{\xi2}, k_{\xi3})$ are used to obtain the desired control velocity and steering angle for accurate trajectory tracking. Although this designed controller algorithm shows that the control system is theoretically stable for any combination of parameter values of , an optimal parameter set needs to be chosen for the stable and accurate execution of the desired trajectories in real-time environment. The chosen parameter values are: $k_{v1} = 0.1; k_{v2} = 0.1; k_{\xi1} = 0.2; k_{\xi2} = 0.2; k_{\xi3} = 0.1$.

A U-shaped trajectory was precomputed and placed in the DDX store to be used as a reference trajectory for the Motion Tracking module. The localization module was operational (including the landmark-based positioning) and used to determine the position of Cycab in the parking lot. Fig.9(a) shows the desired trajectory and executed trajectory with this parameter set. It can be seen that the designed controller has desired performance for executing the planned trajectories. To ensure smooth driving, a first-order low-pass filter is applied to the velocity commands that are sent to the low-level vehicle control module. Fig. 9(c) shows the effects of the filter on the velocity commands (a close-up of the velocity profile is shown in Fig. 9(b).

VII. CONCLUSIONS AND FUTURE WORKS

This paper has presented a novel navigation architecture for automated car-like vehicles in urban environments. Experimental results carried out on a simulation platform in a parking environment has demonstrated the ability to navigate safely in dynamic environments. Preliminary results with a real vehicle were also presented. Future works will include further experiments with a real vehicle.

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