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An Architecture for Automated Driving in Urban Environments

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Summary. 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 decisions *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.

1 Introduction

Autonomous navigation of intelligent vehicles in urban environments 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 [1], the number and variety of autonomous navigation architectures that have been proposed is large (see [2]). 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 [3]. 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* [4, 5, 6, 7], *etc.* Most of today's reactive approaches however face a major challenge: as shown in [8], 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) [9] and Inevitable Collision States (ICS) [10]. PMP is a planning scheme that take into account the real-time constraint explicitly by generating partial motions iterately at each time-step. Like reactive decision schemes, 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 [11] that allows modularity in design and the easy integration of the key functional components required for autonomous navigation: perception, 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 2. The three layers of this architecture are respectively detailed in sections 4, 3 and 5. Experimental results are finally presented in section 6.

2 Navigation Architecture Overview

The architecture presented in this paper is a DDX-based real-time modular architecture. DDX is a publish/subscribe-based middleware [11] 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 5). To complete the architecture,

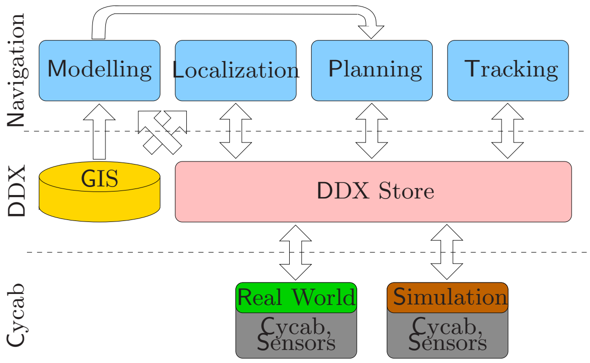


Fig. 1. Functional view of the navigation architecture.

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.

3 Cycab Layer

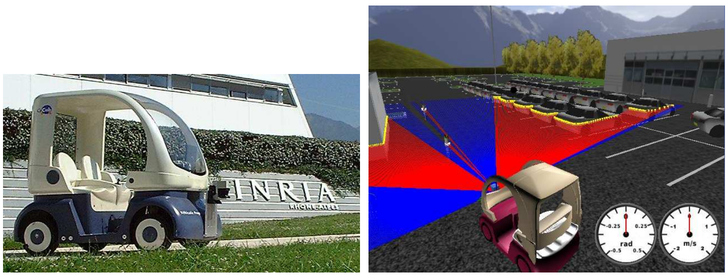


Fig. 2. The Cycab vehicle (left) and the Cycab simulator (right).

3.1 Cycab Vehicle

The Cycab vehicle is a lightweight urban electric vehicle which is specifically designed for downtown areas (Fig.2). 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).

3.2 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 kinematic simulation of the Cycab vehicle, its sensors and its environment. Fig. 2 depicts a snapshot of the simulator GUI (more details at http://cycabtk.gforge.inria.fr).

4 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
- **Trajectory:** nominal trajectory that is to be executed by the vehicle (see section 5.2). 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 1. DDX Store: who is using what?

Module	Input/Output Data
Localization	Input: CycabPose, CycabState, Landmarks, GIS 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

Table 1 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 5.1).

5 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. *World Modelling* and *Motion Planning* are described in the next two sections, while the implementation of *Localization* and *Motion Tracking* modules are omited here. Details can be found in [12] and [13] respectively.

5.1 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.

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. 3-middle). The structure of the roadway is

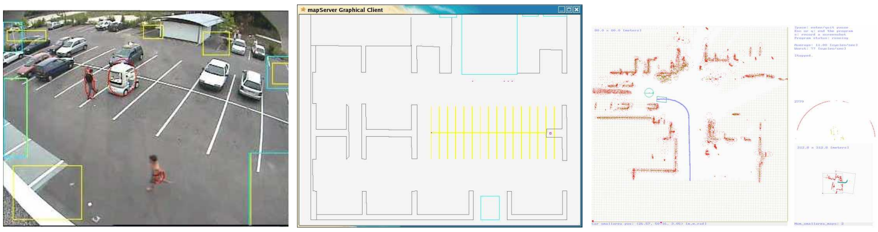


Fig. 3. View of the parking lot (left), of the corresponding map (middle) and of the moving objects tracking process (right).

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 5.2).

In the architecture proposed, it is assumed that the information about the moving objects (linear and/or angular velocity, acceleration, *etc.*) 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). Experiments have been carried out using video cameras and laser range sensor and the tracking techniques presented in [14] and [9] (Fig. 3-right).

Finally, noting that motion planning involves a certain degree of reasoning about the future: you decide now what you will do next, motion prediction regarding the future behaviour of the moving objects is required. 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. The reader is referred to [15] for more details.

5.2 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 1, 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) [9] and Inevitable Collision States (ICS) [10]. 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.

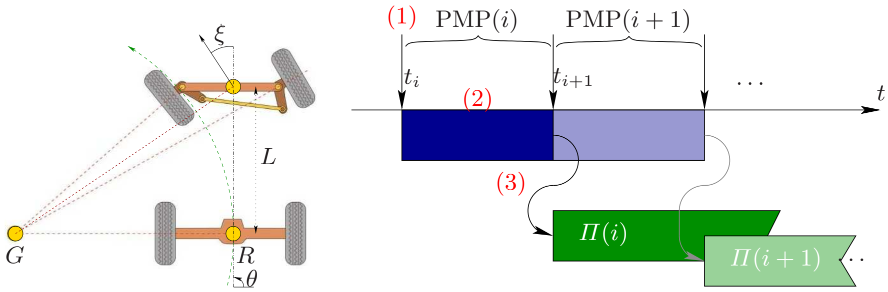


Fig. 4. Model of a car-like vehicle (left), and outline of the Partial Motion Planning iterative cycle (right).

Model of the Vehicle

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. 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 (Fig. 4-left). 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 $\alpha \in [\alpha_{min}, \alpha_{max}]$, $\gamma \in [\gamma_{min}, \gamma_{max}]$, and $|\xi| \leq \xi_{max}$. L is the wheelbase of $\mathcal{A}$.

Partial Motion Planning

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. 4-right depicts the PMP iterative cycle. Let us focus on the planning iteration starting at time ti, it comprises three steps:

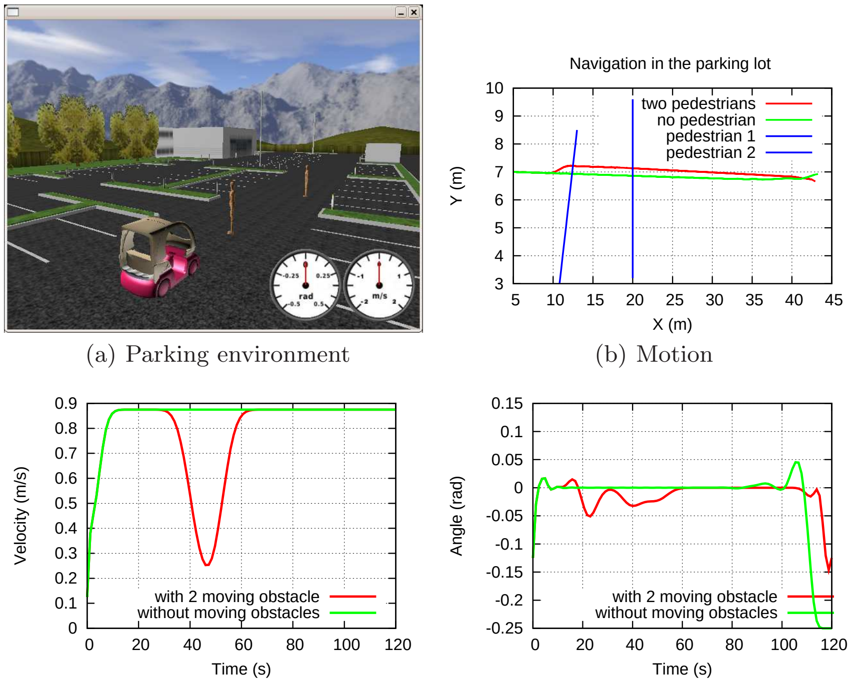
(1) An updated model of the future is acquired (provided by the World Modelling module).
(2) The state-time space of $\mathcal{A}$ is searched using an incremental exploration method that builds a tree rooted at the state $s(t_{i+1})$ with $t_{i+1} = t_i + \delta_p$ where δ_p is the planning time available.
(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 [3] 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 [16] that ensures that $\mathcal{A}$ will never end up in a situation eventually yielding a collision later in the future.

6 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. The PMP cycle is one second and the motion execution step is 50 ms. Autonomous navigation experiments with the real Cycab are underway.

As mentioned earlier, PMP plays a key role for safe navigation in dynamic environments. Simulations for the parking lot scenario of Inria Rhône-Alpes is first studied to test the real-time planning performance of PMP. The simulation environment is a two-dimensional model of the parking lot of Inria Rhône-Alpes (Fig. 5(a)) which is cluttered with twenty-six fixed objects and two pedestrians. The starting pose and the goal pose of the Cycab is $(5, 7, 0)$ and $(43, 7, 0.1)$ respectively. The pedestrians move upwards on the roadway.



(a) Parking environment

(b) Motion

(c) Velocity

(d) Steering angle

Fig. 5. Experiment in the parking lot of Inria Rhône-Alpes.

Fig. 5(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 5(c) and 5(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.

7 CONCLUSIONS AND FUTURE WORKS

This paper has presented a novel navigation architecture for automated car-like vehicles in urban environments. The main feature of this navigation architecture is its ability to make *safe* motion decisions *in real-time*, thus taking into account the harsh constraints imposed by the type of environments considered (partially known with highly dynamic moving objects). Experimental results carried out on a simulation platform in a parking environment has demonstrated the ability to navigate safely in dynamic environments. Future works will include further experiments with a real vehicle.

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