A Real-Time Autonomous Navigation Architecture

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Gang Chen, Thierry Fraichard and Luis Martinez *

* *Inria Rhône-Alpes & LIG-CNRS Lab., Grenoble (FR)*

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 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 are presented.

Keywords: Automated Vehicles; System Architecture; Collision Avoidance.

1. INTRODUCTION

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 (Nilsson, 1984), the number and variety of autonomous navigation architectures that have been proposed is large (see (Nourbaskhsh and Siegwart, 2004)). 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 (Lavalle, 2006). 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* (Khatib, 1986),(Fox *et al.*, 1997),(Fiorini and Shiller, 1998), (Minguez and Montano, 2004), *etc.* Most of today's reactive approaches however face a major challenge: as shown in (Fraichard, 2007), 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) (Benenson *et al.*, Accepted for publication in August 2006) and Inevitable Collision States (ICS) (Fraichard and Asama, 2004). 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 (Corke *et al.*, 2004) 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 3, 4 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 (Corke *et al.*, 2004) 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, 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.

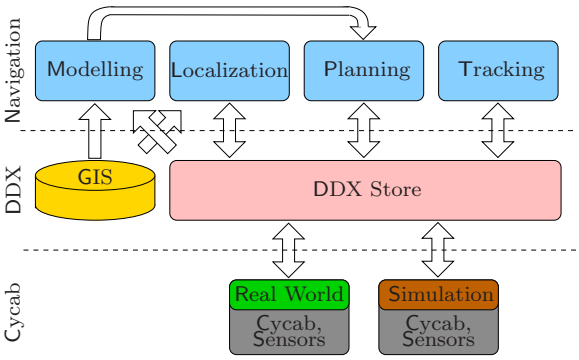


Fig. 1. Functional view of the navigation architecture.

Table 1. 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

3. 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 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).

4. CYCAB LAYER

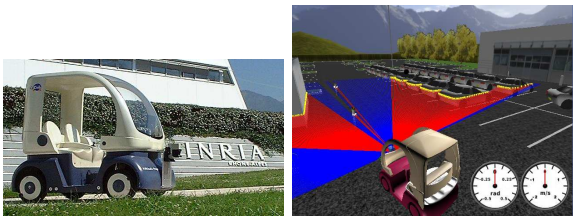


Fig. 2. The Cycab vehicle (left) and the Cycab simulator (right).

4.1 Cycab Vehicle

The Cycab vehicle is a lightweight urban electric vehicle which is specifically designed for downtown areas (Fig.2). It integrates four motor wheels and a motorized mechanical jack for steering. Micro-controllers are used to control of the motorwheels 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).

4.2 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 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).

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. These modules are described in the next sections with a particular emphasis on the "motion" modules.

5.1 World modelling & Localization

These two modules provide the "motion" modules with information about the environment of the vehicle and its localization inside it. 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 5.2).

Due to lack of space, these functionalities are not presented here. The reader is referred to (Chen and Fraichard, 2007) instead.

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) (Benenson *et al.*, Accepted for publication in August 2006) and Inevitable Collision States (ICS) (Fraichard and Asama, 2004). 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.

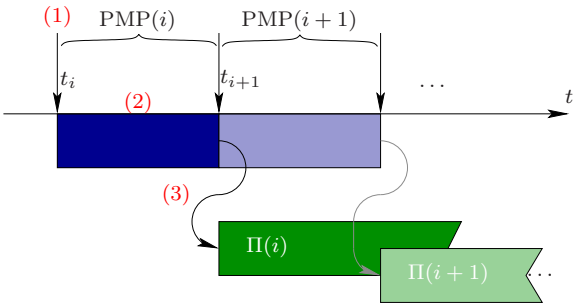


Fig. 3. Partial Motion Planning iterative cycle.

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. 3 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 (Lavalle, 2006) 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 (Parthasarathi and Fraichard, 2007) that ensures that $\mathcal{A}$ will never end up in a situation eventually yielding a collision later in the future.

5.3 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.

The vehicle model used for tracking purposes is the following: a *state* is 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:

$$\begin{cases} \dot{x} = v\cos(\theta) \\ \dot{y} = v\sin(\theta) \\ \dot{\theta} = v\dfrac{\tan\xi}{L} \end{cases} \quad (1)$$

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 (Rives *et al.*, 2005). 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:

$$v_c = v^* - k_v \begin{bmatrix} e_x \\ v - v^* \end{bmatrix}; \xi_c = \xi^* - k_\xi \begin{bmatrix} e_y \\ e_\theta \\ \xi - \xi^* \end{bmatrix} \quad (2)$$

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).

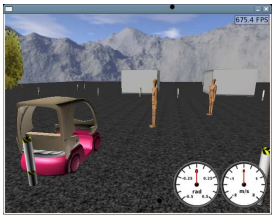
6. EXPERIMENTS

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. So far, only the localization and tracking modules have been tested on the real Cycab. Autonomous navigation experiments with the real Cycab are underway.

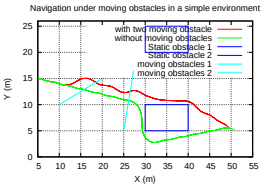
6.1 Simulation Results

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.

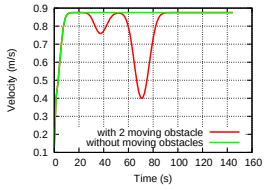
6.1.1. Test Environment



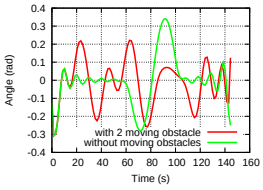
(a) Simple dynamic environment



(b) Motion



(c) Velocity

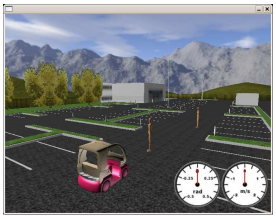


(d) Steering angle

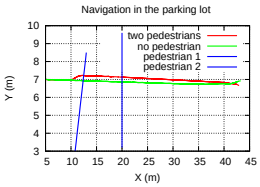
Fig. 4. Experiment in a test environment.

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. 4(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. 4(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 4(c) and 4(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. 4(d)) and slows down twice in order to give way to the moving objects (Fig. 4(c)).

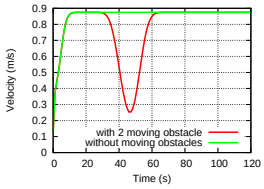
6.1.2. Parking Lot of Inria Rhône-Alpes



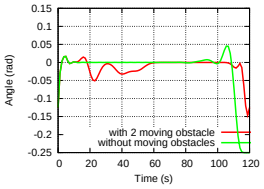
(a) Parking environment



(b) Motion



(c) Velocity



(d) Steering angle

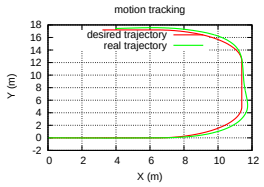
Fig. 5. Experiment in the parking lot of Inria Rhône-Alpes.

The second experiment is done in a two-dimensional model of the parking lot of Inria Rhône-Alpes (Fig. 5(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 the goal pose of the Cycab is $(5, 7, 0)$ and $(43, 7, 0.1)$ respectively. The pedestrians move upwards on the roadway. 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.

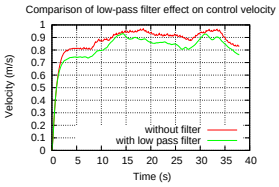
6.2 Real Experiments

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 described in section 5.3, five control controller parameters are used to obtain the desired control velocity and steerting angle for accurate trajectory tracking (Equation. 3).

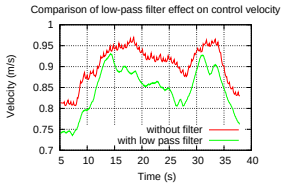
$$\begin{aligned} v_c &= v^* - (k_{v1} e_x + k_{v2}(v - v^*)) \\ \xi_c &= \xi^* - (k_{\xi 1} e_y + k_{\xi 2} e_\theta + k_{\xi 3}(\xi - \xi^*) \end{aligned} \quad (3)$$



(a) Tracking results



(b) Filtered *vs* non-filtered velocity profiles



(c) Velocity profiles close-up

Fig. 6. Tracking of a U-shaped trajectory.

Although this designed controller algorithm shows that the control system is theoretically stable for any combination of parameter values of $(k_{v1}, k_{v2}, k_{\xi 1}, k_{\xi 2}, k_{\xi 3})$, 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 $k_{v1} = 0.1; k_{v2} = 0.1; k_{\xi 1} = 0.2; k_{\xi 2} = 0.2; k_{\xi 3} = 0.1$.

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.6(a) shows the desired trajectory and excuted 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. 6(c) shows the effects of the filter on the velocity commands (a close-up of the velocity profile is shown in Fig. 6(b).

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.

REFERENCES

Benenson, R., S. Petti, Th. Fraichard and M. Parent (Accepted for publication in August 2006). Toward urban driverless vehicles. *Int. Journal of Vehicle Autonomous Systems*.

Chen, G. and Th. Fraichard (2007). A real-time navigation architecture for automated vehicles in urban environments. In: *Proc. of the IEEE Intelligent Vehicles Symposium*. Istanbul (TR).

Corke, P., P. Sikka, J. Roberts and E. Duff (2004). DDX: A distributed software architecture for robotic systems. In: *Proc. of the Australian Conf. on Robotics and Automation*. Canberra (AU).

Fiorini, P. and Z. Shiller (1998). Motion planning in dynamic environments using velocity obstacles. *Int. Journal of Robotics Research* **17**(7), 760–772.

Fox, D., W. Burgard and S. Thrun (1997). The dynamic window approach to collision avoidance. *IEEE Robotics and Automation Magazine* **4**(1), 23–33.

Fraichard, Th. (2007). A short paper about safety. In: *Proc. of the IEEE Int. Conf. on Robotics and Automation*. Rome (IT).

Fraichard, Th. and H. Asama (2004). Inevitable collision states - a step towards safer robots?. *Advanced Robotics* **18**(10), 1001–1024.

Khatib, O. (1986). Real-time obstacle avoidance for manipulators and mobile robots. *Int. Journal of Robotics Research*.

Lavalle, S. (2006). *Planning Algorithms*. Cambridge University Press.

Minguez, J. and L. Montano (2004). Nearness diagram (ND) navigation: collision avoidance in troublesome scenarios. *IEEE Trans. on Robotics and Automation* **20**(1), 45–59.

Nilsson, N. J. (1984). Shakey the robot. Technical note 323. AI Center, SRI International. Menlo Park, CA (US).

Nourbaskhsh, I. R. and R. Siegwart (2004). *Introduction to Autonomous Mobile Robots*. MIT Press.

Parthasarathi, R. and Th. Fraichard (2007). An inevitable collision state-checker for a car-like vehicle. In: *Proc. of the IEEE Int. Conf. on Robotics and Automation*. Roma (IT).

Rives, P., S. Benhimane, E. Malis and J.R. Azinheira (2005). Vision-based control for car platooning using homography decomposition. In: *Proc. of the IEEE Int. Conf. on Robotics and Automation*. Barcelona ES). pp. 2173–2178.