

Research Activity Summary

Thierry Fraichard — April 2013

Robotics and **Motion** are the two keywords that best capture the scope of my research activities. I have decided to present my work in this area starting with an overall overview organized thematically rather than chronologically (§1). Afterwards, I focus on five selected results which I believe are important and representative of the quality and variety of my research activities. These results are different in nature and comprise to varying degrees scientific contributions, software/hardware technology developments and industrial transfers:

- Scientific contribution:
 1. **Inevitable Collision States**, a concept to address motion safety (§2).
- Scientific contribution and software technology development:
 2. **Growing Hidden Markov Models**, an HMM extension applied to long-term future motion prediction (§3).
 3. **CC-Steer**, a steering method for nonholonomic systems (§4).
- Scientific contribution, software technology development and industrial transfer:
 4. **Bayesian Occupancy Filter**, a software framework for sensor-fusion and dynamic environment modelling (§5).
- Software and hardware technology development:
 5. **Parkview**, a platform for the interpretation of complex dynamic scenes (§6).

In each case, I detail the difficulty of the problem addressed, the originality of the result obtained and my actual contribution to it. I also discuss its impact in the scientific community.

Video sequences illustrating different aspects of these contributions can be found on the following web-page:

<http://thierry.fraichard.free.fr/research>

1 Overview

Motion planning is the core of my research work. Given a model of a robot and a model of its environment, it consists in computing the motion that will take the robot from, say, A to B . Although motion planning can be viewed as an abstract, model-based and standalone problem, a motion planner will eventually be one component of the overall control architecture of a real robot. Bearing this in mind, I have always sought to integrate into motion planning the different constraints linked to the actual robot at hand and its environment. From the beginning, I have focused on motion planning for wheeled mobile robots with automated cars as the primary target application. Accordingly, I have tried to tackle all the constraints corresponding to this challenging problem (kinematic and dynamic constraints, moving obstacles, uncertainty). Later, I expanded the field of my research activities in order to address problems that are not about motion planning *per se* but concern the model that motion planning requires, *i.e.* the model of the environment. My main contributions concern different aspects of these problems, they are presented thematically in the next sections.

1.1 Path Planning

Path planning focuses on the geometric aspects of motion planning: it aims at computing the geometric curve that will take the robot from A to B without colliding with the fixed obstacles around.

My first contribution to path planning has to do with **nonholonomy**. The problem is to compute path for robots that better take into account their kinematic properties and, in particular, the nonholonomic constraints that restrict their motions. This contribution is detailed in the Key Contribution #3.

My second contribution to path planning has to do with **path robustness**. The challenge here is to compute paths whose execution can be guaranteed to succeed in spite of the uncertainty affecting

the control and the sensing of the actual robot. Robustness in motion planning was addressed first in the context of assembly tasks with manipulator arms (mid 70's), mobile robots were considered later (90's). Given the intrinsic complexity of robust motion planning, simplifying assumptions would usually be made, *e.g.* omnidirectional point robot, perfect sensing. Such assumptions could seriously reduce the applicability to real problems of the solutions proposed. The omnidirectional robot assumption for instance would stumble upon the fact that most wheeled mobile robots are subject to nonholonomic constraints.

To address this issue, I introduced nonholonomic constraints in robust path planning and proposed novel robust path planning solutions for car-like vehicles subject to sensing and localization uncertainty (odometric drift). The challenges here were (1) to consider realistic sensor models, and (2) to establish uncertainty evolution models adapted to nonholonomic robots. This work started with Raphaël Mermond's PhD [1] using geometric uncertainty evolution models. Later, in cooperation with Alain Lambert, we shifted to probabilistic models [2]. In both cases, the uncertainty evolution model was coupled with a nonholonomic path generation method and embedded in a generic motion planning scheme so as to obtain a robust collision-free path planner.

1.2 Trajectory Planning

A trajectory can be thought of as a path with a time history. In other words, it specifies where the robot should pass but also when and how. Trajectory planning is in order as soon as you have to deal with dynamic constraints. Dynamic constraints come in two flavors: those related to the robot's dynamics, *e.g.* bounds on its velocity/acceleration, and those related to the environment, *i.e.* the moving obstacles. Given my target application, *i.e.* automated cars, I had to consider both type of constraints simultaneously. When I started to work on this topic during my PhD [3], I could locate only two research works (of limited interest) dealing with both type of dynamic constraints [4, 5]. The intrinsic complexity of such trajectory planning problems certainly explained this situation.

The primary contribution of my PhD was to introduce and show how the **state-time space** framework could be used to tackle complex motion planning problems featuring robots subject to kinematic/dynamic constraints and moving in dynamic environments. In a sense, the state-time space (STS) is for trajectory planning the equivalent of the configuration space for path planning [6]. In STS, part of the constraints at hand (dynamics and moving obstacles) are represented uniformly as forbidden regions and trajectory planning boils down to finding a curve in the free part of STS. Accordingly, standard path planning techniques can be adapted to solve the problem at hand. This work was finalized by an article published in Advanced Robotics [7]. At the time of my PhD, the high dimensionality of STS was a limiting factor. However, the advent of stochastic motion planning techniques in the late 90's has changed the situation dramatically: suddenly, it became possible to efficiently handle high dimensionality spaces [8, 9]. And STS became the natural framework to address trajectory planning problems with dynamic constraints as indicated by the number of research works using STS that have appeared since then, *e.g.* [10, 11, 12, 13].

When a motion is planned in an environment featuring moving obstacles, it must be temporally anchored. In other words, it must start at a prescribed time and every position along the motion must be reached by the robot at the time prescribed. Temporal anchoring is required to ensure no collision with the moving obstacles. In these circumstances, the motion planning process is subject to a hard real-time constraint henceforth called **decision time constraint**: the time available to plan the motion is upper-bounded by the duration between the current time and the time at which the motion is supposed to start. If it were possible to set the start time arbitrarily, that would not be a problem. It is not the case unfortunately: among moving obstacles, a robot cannot remain passive since it runs the risk of being hit. To a large extent, the characteristics of the moving obstacles determine the decision time constraint. Needless to say, on the roadway the decision time constraint is stringent.

In spite of its importance, the decision time constraint was strangely absent from the works on motion planning in dynamic environments. My first contribution here has been to make this constraint explicit. Now, given the intrinsic complexity of motion planning, there is little hope that an arbitrarily low decision time constraint can ever be met. Having acknowledged that, my second contribution was to propose **partial motion planning** (PMP) as an answer to this issue. PMP is an interruptible motion planning scheme: when the decision time is over, PMP returns the best motion it has computed so far, it may be partial only though and not go all the way to the goal but, at least, PMP ensures that the decision time

constraint is met (and that the safety of the robot is not compromised). Of course, PMP has to be called repeatedly until the goal is reached. At each cycle, the partial motion produced is passed to the robot for execution. I introduced PMP in 2001 [14]. The first application of PMP was made in collaboration with Frédéric Large, a PhD student of my former team E-MOTION [15, 16]. Later, I furthered this work with Stéphane Petti's PhD [17], it involved experiments on a real vehicle [18].

1.3 Motion Safety

The aforementioned decision time constraint is such that, if it is violated, the safety of the robot is compromised. This observation led me to consider more carefully what motion safety could mean for a robot. This is an issue that goes well beyond motion planning and that actually concerns autonomous navigation as a whole. This contribution is detailed in the Key Contribution #1.

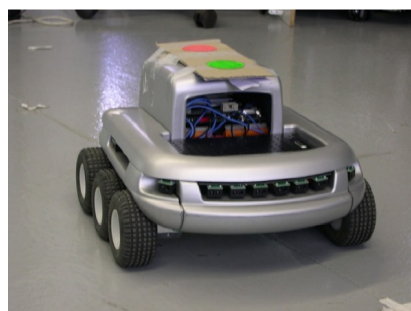
1.4 Dynamic World Modelling and Future Prediction

This last section is not about motion planning *per se*. It is concerned with the environment models that motion planning requires as input. My first contribution here concerns the **modelling of dynamic environments**. It is detailed in the Key Contribution #4. My second contribution has to do with **future motion prediction**. It is detailed in the Key Contribution #2.

1.5 Technology developments



(a) Ligier



(b) Koala



(c) Cycab



(d) Wheelchair

Figure 1: Experimental platforms.

Robotics is ultimately about making actual robots that do things. To that end, I have always pushed to have my research ideas implemented and evaluated on real robots. Getting a robotic platform up and running takes a lot of time and efforts. To test a navigation scheme for instance, one has to take care of aspects such as sensor data processing, robot localization, environment mapping, trajectory following and so forth. The software modules corresponding to these functionalities have to be implemented and integrated in an overall control architecture. This additional work is a time-consuming and somewhat unrewarding process. It is nonetheless mandatory if one's want to confront its theories to real-world

constraints and validate them. Over the years, four different robotic platforms have been used to test the different motion planning and navigation approaches I have proposed (see Fig. 1):

- (a) **Ligier** electric car: used to test the Fuzzy Logic-based navigation scheme developed in the scope of the PhD of Philippe Garnier [19].
- (b) **Koala** mobile robot: used to test the Markov Decision Process-based navigation scheme developed in the scope of the Master of Julien Burlet [20].
- (c) **Cycab** electric cart: used to test the Partial Motion Planning-based navigation scheme developed in the scope of the PhD of Stéphane Petti [17].
- (d) Bluebotics' automated **wheelchair**: used to test the Trajectory Deformation-based navigation scheme developed in the scope of the PhD of Vivien Delsart [21], and the Inevitable Collision State-based navigation scheme developed in the scope of the PhD of Luis Martinez of [22]. This platform was also used for the workshop of the 2010 edition of the Fête de la science.

2 Key Contribution #1: Inevitable Collision States

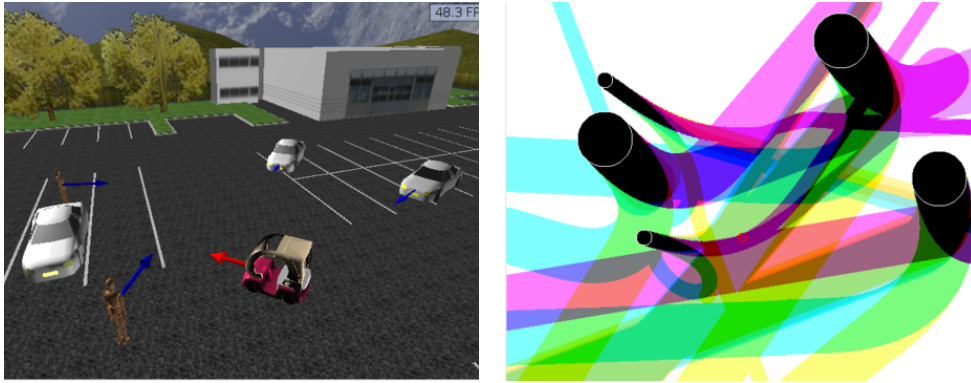


Figure 2: (left) a driving situation involving fixed and moving obstacles; (right) the corresponding Inevitable Collision States (black areas – bird's-eye view).

2.1 Description of the contribution

An Inevitable Collision State (ICS) for a robot is a state such that, no matter what the future trajectory of the robot is, a collision eventually occurs with an obstacle of the environment. The ICS concept applies to arbitrary robots and arbitrary environments (with fixed and moving obstacles). Besides offering new insights into the complexity of safely moving in dynamic environments, the ICS concept provides a theoretical answer to the motion safety issue: for its own safety and that of its environment, a robot should never move to a state which is an ICS. Accordingly, the ability for a robot to characterize the ICS set in its reachable state space becomes essential. Given an ICS-Checker, *i.e.* an algorithm that determines whether a given state is an ICS or not, it becomes possible to design navigation systems for which *motion safety is guaranteed*.

2.2 Own contribution

The ICS concept stems from a reflection I had in the mid 00's about the motion safety of robots. I formalized this concept on my own and furthered it afterwards in the scope of various internships and PhDs (Rishikesh Parthasarathi, Antoine Durand-Gasselin, Joël Schaerer, Stéphane Petti, Luis Martinez, Antoine Bautin and Sara Bouraine).

2.3 Originality and difficulty

I came up with the ICS concept when I noticed that motion safety is a term that is widely used in Robotics and never defined. The study of the literature I performed at the time revealed that motion

safety analysis is usually overlooked or taken for granted. It does not mean that motion safety is not a concern (quite the contrary). It is just that no attempt is made at characterizing the conditions under which collisions will be avoided. Interestingly enough, I also established that a number of state-of-the-art navigation schemes are in fact unsafe in dynamic environments (in the sense that it is easy to come up with situations where a collision will take place) [23]. The ICS concept helps in understanding the difficulty of obtaining motion safety guarantee in real-world situations. It also outlines two important facts about motion safety: (1) the necessity to reason about the future, and (2) to do so with an appropriate lookahead, *i.e.* the duration over which the future is considered. Although related concepts existed in the literature, *e.g.* [24, 25, 26], it seems that their consequences regarding motion safety within dynamic environments never surfaced. In this respect, I believe my work around the ICS concept is important. From a practical point of view, characterizing the ICS set of a given robot in a given environment is a complex problem that remains largely open. In principle, it requires a model of the future (possibly up to infinity), and to consider all future trajectories of the robot at hand. In practice however, the properties I have established in [27] have permitted the design of ICS-Check, the first ICS-checker, *i.e.* an algorithm that determines whether a given state is an ICS or not [28]. ICS-Check is generic and efficient, it will be the core component of an autonomous navigation scheme in dynamic environments with guaranteed motion safety properties.

2.4 Validation and impact

The PhD work on autonomous navigation in dynamic environments of Stéphane Petti was the first practical implementation of the ICS concept with experiments on a real vehicle [17]. My ICS-related papers are regularly cited by the latest works on navigation in dynamic environments. There is a growing awareness in the Robotics community of the particulars of dynamic environments and the necessity to design navigation strategies with certain motion safety guarantees. I have organized the first two workshops on this topic¹ and edited a special issue on motion safety for the Autonomous Robot journal [29].

2.5 Dissemination

Following the initial journal article presenting the ICS concept [27]², the progress in the development of the ICS has been documented in a series of publications in the major international conferences in the field: [31, 32, 28, 33, 30]. A journal article has been published in the Autonomous Robot journal [34], another article has been submitted to *IEEE Trans. on Robotics*.

3 Key Contribution #2: Growing Hidden Markov Models

3.1 Description of the contribution

Motion safety and ICS characterization (see Key Contribution #1) require information about the future motion of moving objects. In most real applications however, this information is not available beforehand and one has to resort to motion prediction instead. The Growing Hidden Markov Model (GHMM) has been developed to address this question: how to predict the long-term future behaviour of the moving objects (Fig. 3-left)? The GHMM is an extension to the standard Hidden Markov Model which is a popular tool in Pattern Recognition [35]. It has been used to learn the typical motion patterns of the moving objects in a given environment using as input a collection of observed trajectories (Fig. 3-center). Once learned, the motion patterns are used to predict the future behaviour of the moving objects (Fig. 3-right). The software implementation of GHMM yielded a software package that has been distributed.

3.2 Own contribution

I initiated the work on future motion prediction topic during the Master internship of Dizan Vasquez [36]. The development of the GHMM and its application to future motion prediction has been done in the

¹<http://safety2010.inrialpes.fr>, <http://safety2011.inrialpes.fr>.

²This article is in a special issue featuring selected articles from the Int. Conf. on Intelligent Robots and Systems (IROS) [30].



Figure 3: (left) the long-term future motion prediction problem; (center) set of pedestrian trajectories observed on a parking lot; (right) GHMM prediction of the future motion of the currently observed pedestrian (estimation of the state at time $t + 10$ and of the goal state).

scope of the PhD of Dizan Vasquez whom I supervised [37].

3.3 Originality and difficulty

Motion prediction is a very active research domain. Due to the difficulty of modeling the various factors that determine the motion of an object, most long-term motion prediction techniques aim at learning the typical motion patterns of the moving objects in a given environment using as input a collection of observed trajectories. Once learned, the motion patterns are used to predict the future behaviour of the moving objects, *e.g.* [38, 39, 40]. Unlike most current techniques that use off-line and batch learning algorithms, the GHMM is able to learn new motion patterns in an on-line and continuous fashion. Accordingly, when new motion patterns appear, they can be learned. Likewise, obsolete motion patterns can be forgotten. Besides the GHMM has the ability to perform both learning and prediction in parallel. As mentioned above, the GHMM is an extension to the standard Hidden Markov Model. One of its distinctive feature is that both the structure and the parameters of the corresponding HMM can be learned simultaneously. This property is obtained thanks to the use of a Self-Organizing Topological Map [41]. Accordingly, the GHMM is suited to tackle any pattern recognition problem for which there is a topological equivalence between a continuous state space and the corresponding observation space.

3.4 Validation and impact

The GHMM has first been validated on the ParkView platform (see Key Contribution #5). The GHMM in particular and motion prediction in general have now become central in the work of the E-MOTION team (see for instance the PhD work on autonomous navigation of Chiara Fulgenzi [42] or the PhD work on risk assessment of Christopher Tay [43]). Another interesting by-product of the GHMM technology is the use of the Self-Organizing Topological Map to solve on object extraction problem in video sequences [44]. Following the post-doc stay of Dizan Vasquez in the Autonomous Systems Lab. of the Swiss Federal Inst. of Technology (ETH) in Zürich, the GHMM is now used there in the scope of their Smarter automated car initiative. The GHMM has also been selected by the Field Robotics Center of Carnegie Mellon University as a benchmarking tool for motion prediction techniques. Finally, let us emphasize that the PhD of Dizan Vasquez received the **European Robotics PhD Award** in April 09.

3.5 Dissemination

The progress in the development of the GHMM and its application to long-term future motion prediction has been documented in a series of publications in the major international conferences in the field: [45, 46, 47, 48] and in book chapters in the *Springer STAR* series [49, 50]. It culminated in two articles published in the top ranking international journals *Int. Journal of Robotics Research* [51] and *IEEE Trans. on Intelligent Transportation Systems* [52]³. As a recipient of the 2009 European Robotics PhD

³This article is in a special issue featuring selected articles from the Int. Symp. on Robotics Research (ISRR) [45].

Award, Dizan Vasquez had the opportunity to publish a revised version of his PhD thesis as a book in the *Springer STAR* series [53].

Dizan Vasquez also developed a distributable version of the GHMM software (Debian package). It is freely distributed as an Open-Source software and available at <https://github.com/dichodaemon/ghmm>.

4 Key Contribution #3: CC-Steer

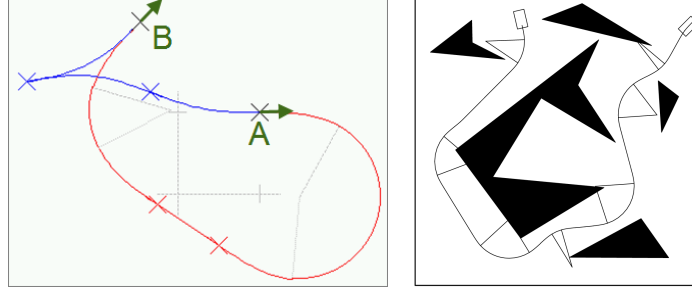


Figure 4: (left) CC-Steer on its own; (right) coupled with a generic motion planning scheme.

4.1 Description of the contribution

Path planning is aimed at computing the geometric path that will take a robot from A to B without colliding with fixed obstacles. *Nonholonomic Path Planning* (NPP) is a branch of path planning concerned with robots that are nonholonomic, *i.e.* subject to first-order kinematic constraints that restrict the motion they can make⁴. NPP emerged in the mid-eighties [54]. It is an important research topic since almost all wheeled mobile robots are nonholonomic. The standard way to address NPP is to design a *steering method*, *i.e.* an algorithm that computes nonholonomic paths in the absence of obstacles, and to embed it within a generic motion planning scheme, *e.g.* [55, 8, 56, 9], in order to take the obstacles into account and obtain a collision-free path. CC-Steer is a steering method designed for nonholonomic robots whose kinematics is similar to that of a car. The paths computed by CC-Steer are made up of straight segments, circular arcs and clothoidal transitions (Fig. 4-left). When embedded within a general motion-planning scheme, CC-Steer yields a collision-free path planner (Fig. 4-right). The software implementation of CC-Steer yielded a software package that has been distributed.

4.2 Own contribution

The development of CC-Steer started in the scope of the PhD of Alexis Scheuer whom I supervised [57]. To begin with, we addressed the case of a car moving forward only. I later addressed the case of the car moving both forward and backward with two interns: Richard Desvigne [58] and Pierre Billiau. I finalized the scientific work with an article published in the *IEEE Trans. on Robotics* [59]. Different versions of the software have been developed over the years. I have written the final version with the features described in [59]. The code is about 6000 lines long.

4.3 Originality and difficulty

When we started to explore path planning for cars, most existing path planners would consider a simplified car model and compute paths made up of circular arcs connected with tangential straight segments (such paths are optimal in length and easy to compute [60]). However, such paths have a serious drawback: their curvature profile is discontinuous meaning that, if a car has to follow such a path accurately, it must stop at each segment-arc transition in order to reorient its wheels. To address this issue, we had to use a more complex car model. After having established the key properties of this new model, we designed CC-Steer that compute paths that satisfy the following properties: (1) continuous curvature,

⁴Consider a single wheel for instance, it must always move in a direction perpendicular to its rotational axis.

(2) upper-bounded curvature (to account for the steering angle limits), and (3) upper-bounded curvature derivative (to account for the steering velocity limits). Accordingly such paths can be *tracked accurately with a guaranteed minimum velocity*. On top of that, we have established that CC-Steer verifies a topological property that ensures that it is *complete* (in the sense that it can connect arbitrary pairs of configurations) and that, when it is used within a general motion-planning scheme, it yields a *complete collision-free path planner*. Finally, the length of the paths computed *converges towards the optimum* when the curvature derivative increases. As of today and to the best of my knowledge, CC-Steer remains the only steering method verifying all the aforementioned properties.

4.4 Validation and impact

CC-Steer has been used within the E-MOTION team and also by the IMARA team in Paris [18]. In the wake of the publication of my work on continuous-curvature path planning, I have been regularly contacted by researchers interested in this software. I am aware of two publications wherein CC-Steer has actually been used to support research activities: [61, 62]. CC-Steer remains one of my most cited work (one of the oldest too).

4.5 Dissemination

The progress in the development of CC-Steer has been documented in a series of publications in the major international conferences in the field: [63, 58, 64, 65, 66]. It culminated in an article published in the top ranking international journal *IEEE Trans. on Robotics* [59]. The CC-Steer software package is available on request. It is freely distributed as an Open-Source software.

5 Key Contribution #4: Bayesian Occupancy Filter

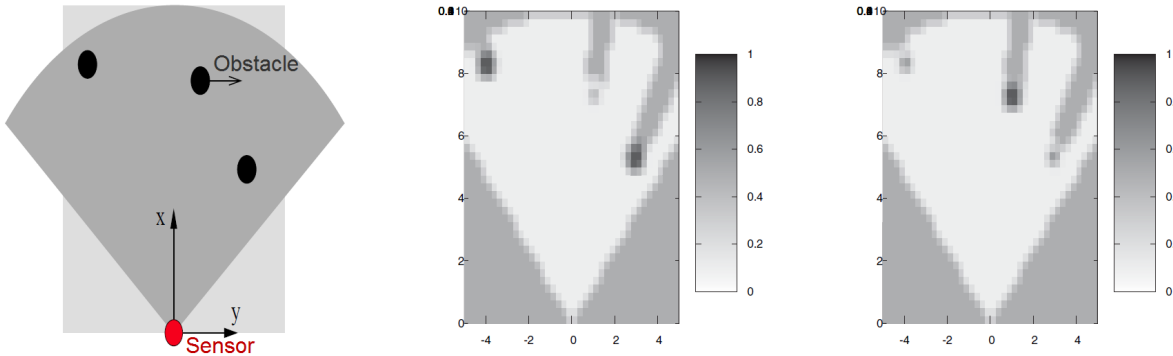


Figure 5: (left) situation observed, the sensor observations are given as $\{x, y, \dot{x}, \dot{y}\}$. The moving obstacle is moving to the right with a unit speed; (center and right) occupancy probabilities for two slices of the four-dimensional BOF grid, *i.e.* for all possible positions at a given velocity: (center) $\{\dot{x} = 0, \dot{y} = 0\}$; (right) $\{\dot{x} = 0, \dot{y} = 1\}$.

5.1 Description of the contribution

The Bayesian Occupancy Filter (BOF) is a software framework for robust perception and modelling of highly dynamic environments. It combines the probabilistic occupancy grid framework⁵ with Bayesian Filtering techniques. Unlike standard occupancy grids, the BOF maintains a four-dimensional grid featuring the objects' position and their velocity (Fig. 5). It is at the origin of a technology transfer with the Probayes company⁶.

⁵That models the environment as a discrete grid with occupancy probability attached to each cell.

⁶<http://www.probayes.com>.

5.2 Own contribution

My primary contribution to the BOF stems from my role as the coadvisor of the PhD of Christophe Coué [67]. His PhD was supported by the European project FP6-IST-12224 **Carsense**, “Sensing of Car Environment at Low Speed Driving” [Jan. 00–Dec. 02]. As the leader of the workpackage “Sensor Data Fusion” within Carsense, I pushed for the development of the deliverable that would become the prototype of the BOF. The BOF software has been patented by INRIA: patent #FR0552735, “Procédé d’assistance à la conduite d’un véhicule et dispositif associé” (registered on 9 September 09). I am coinventor for this patent.

5.3 Originality and difficulty

Reliable and efficient perception and modelling of dynamic outdoor environments is increasingly being addressed, *e.g.* [68, 69, 70] or the solutions developed for the 2007 DARPA Urban Challenge [71, 72, 73]. However, it remains largely an open problem in dynamic and densely cluttered environments (such as crowded urban driving scenes). Adding the velocity dimension to the occupancy grid is one of the distinctive features of the BOF framework. Coupling it with the use of Bayesian Filtering techniques helps to increase the robustness of the model with respect to occlusions, appearances and disappearances of objects. The BOF captures all the relevant information on the system’s environment; this information includes the description of the occupied areas, of the unoccupied areas, and of the hidden areas, *i.e.* areas of the environment that are temporarily hidden from sensors by an obstacle (see the video illustrating the occluded obstacle avoidance experiment reported in [74]). The BOF also allows the straightforward fusion of the information acquired through different sensors, *e.g.* video cameras, range sensors. The BOF can be used for any application requiring the ability to detect and track moving objects, to estimate their positions, and to predict their future motions.

5.4 Validation and impact

The BOF is now commercialized by the Probayes company, a former spin-off of E-MOTION. The activity of Probayes is based upon three core technologies and the BOF is one of them. The BOF is an important asset for Probayes. It provided the company with the opportunity to obtain a series of contracts related to automotive safety with major players of the automotive industry: Toyota, Denso and Hitachi. As of today, the collaboration between E-MOTION and Probayes around the BOF continues.

5.5 Dissemination

The progress in the development of the BOF has been documented in a series of publications in the major international conferences in the field: [75, 76, 77, 78] and in a book of the *Springer STAR* series [79]. It culminated in an article published in the top ranking international journal *Int. Journal of Robotics Research* [74]⁷. BOF++, an optimized version of the BOF, was later developed in collaboration with Emanuel Yguel and Kamel Mekhnacha from Probayes. BOF++ has also been patented by INRIA (patent #FR0552736). As of 2008, INRIA has granted Probayes the exploitation licence for the BOF++ which is now on the catalogue of products of Probayes.

6 Key Contribution #5: ParkView

6.1 Description of the contribution

ParkView is an experimental platform combining both hardware and software aspects. It was originally developed to support the research activities carried out in the French Project ROBEA ParkNav, “Interpretation of Complex Dynamic Scenes and Reactive Motion Planning” [Oct. 02–Sep. 05]. At the end of the project, ParkView comprised seven video cameras observing the parking lot of the INRIA Grenoble Rhône-Alpes Research Center from different angles (Fig. 6-left and center). The different video streams were merged, processed and interpreted in order to feed a Map Server, *i.e.* a software module providing

⁷This article is in a special issue featuring selected articles from the Int. Conf. on Field and Service Robotics (FSR) [75].



Figure 6: The ParkView platform: Parking lot — Cameras — Map server.

in real-time a model of the parking lot combining information about its structure and about the moving objects (position and velocity) (Fig. 6-right).

6.2 Own contribution

I was the project manager responsible for the design of the platform. I selected and supervised the two engineers, Frédéric Hélin and Eric Boniface, and the post-doc, Fernando De La Rosa, that worked on the platform during the 2002-2006 period. As the leader of the ParkNav project, I was also in charge of the coordination with the partners of the ParkNav project. A total of 16500 lines of code including comments have been written for ParkView.

6.3 Originality and difficulty

The Map Server was the core and original part of ParkView. At the time, there was no such software available. ParkView was primarily a testbed aimed at hosting for evaluation purposes the software components developed by the ParkNav partners working on image-processing. The primary issue in ParkView was integration: the components provided by the partners were research prototypes that had to be redesigned in order to fit the ParkView architecture and the requirements of the target application, *i.e.* the Map Server. Adapting laboratory image-processing techniques to the harsh requirements of an outdoor environment proved particularly hard.

6.4 Validation and impact

The people involved in ParkView were all the partners involved in the ParkNav project, namely:

- LAAS-CNRS Toulouse, group Robotics and Artificial Intelligence.
- INRIA Grenoble, E-MOTION, MOVI and PRIMA teams and SED support group.
- INRIA Rennes, LAGADIC team.

LAGADIC, MOVI and PRIMA brought their image-processing expertise to the project. It is their technologies, calibration tools and visual trackers mostly, that had to be integrated into ParkView and adapted so as to operate outdoors reliably. At the end of the project, the Map Server was working well and proved useful for future motion prediction and autonomous navigation purposes.

LAAS-CNRS and E-MOTION were the users of the platform. They used the information provided by the Map Server as input for their research in motion prediction (E-MOTION) and autonomous navigation (E-MOTION and LAAS-CNRS). Joint experiments in autonomous navigation were carried out with ParkView [80].

6.5 Dissemination

Two webpages have been set up to respectively describe the ParkView platform and the ParkNav project:

- <http://emotion.inrialpes.fr/parknav> and <http://emotion.inrialpes.fr/parkview>.

Two technical reports document the engineering work that has been produced [81, 82]. After the end of the ParkNav project in Sep. 05, the platform ParkView has been kept alive and maintained by E-MOTION for its own research purposes (future motion prediction, autonomous navigation in dynamic environments). It was also used by PRIMA (detection and tracking of moving objects). The ParkView platform was decommissioned in 2008.

References

- [1] Th. Fraichard and R. Mermond. Path Planning with Uncertainty for Car-Like Robots. In *IEEE Int. Conf. on Robotics and Automation*, 1998.
- [2] A. Lambert and Th. Fraichard. Landmark-Based Safe Path Planning for Car-Like Robots. In *IEEE Int. Conf. on Robotics and Automation*, 2000.
- [3] Th. Fraichard. *Planification de mouvement pour mobile non-holonyme en espace de travail dynamique*. Thèse de doctorat, Inst. Nat. Polytechnique de Grenoble, Grenoble (FR), April 1992.
- [4] C. O'D'unlaing. Motion planning with inertial constraints. *Algorithmica*, 2, 1987.
- [5] K. Fujimura and H. Samet. A hierarchical strategy for path planning among moving obstacles. *IEEE Trans. Robotics and Automation*, 5(1), February 1989.
- [6] T. Lozano-Perez. Spatial planning, a configuration space approach. *IEEE Trans. on Computing.*, 32(2), February 1983.
- [7] T. Fraichard. Trajectory planning in a dynamic workspace: a 'state-time space' approach. *Advanced Robotics*, 13(1):75–94, 1998.
- [8] L. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars. Probabilistic roadmaps for path planning in high dimensional configuration spaces. *IEEE Trans. Robotics and Automation*, 12, 1996.
- [9] S. Lavalle and J. J. Kuffner. Rapidly-exploring random trees: Progress and prospects. In B. R. Donald, K. M. Lynch, and D. Rus, editors, *Algorithmic and Computational Robotics: New Directions*. A. K. Peters, 2001.
- [10] E. Frazzoli, M. A. Dahleh, and E. Feron. Real-Time Motion Planning for Agile Autonomous Vehicle. In *Proc. of the American Control Conf.*, Arlington, VA (US), June 2001.
- [11] J. Bruce and M. Veloso. Real-time randomized path planning for robot navigation. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, Lausanne (CH), October 2002.
- [12] D. Hsu, R. Kindel, J.-C. Latombe, and S. Rock. Randomized kinodynamic motion planning with moving obstacles. *Int. Journal of Robotics Research*, 21(3), March 2002.
- [13] J.P. van den Berg and M.H. Overmars. Roadmap-based motion planning in dynamic environments. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, Sendai (JP), October 2004.
- [14] Sharp. Programmation automatique et systèmes décisionnels en robotique. Rapport d'activité annuel, Inst. Nat. de Recherche en Informatique et en Automatique, 2001.
- [15] F. Large. *Navigation Autonome d'un Robot Mobile en Environnement Dynamique et Incertain*. PhD Thesis, Université de Savoie, Chambéry (FR), November 2003.
- [16] D. Vasquez, F. Large, Th. Fraichard, and C. Laugier. High-Speed Autonomous Navigation with Motion Prediction for Unknown Moving Obstacles. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 2004.
- [17] S. Petti. *Partial Motion Planning Framework for Safe Navigation in Dynamic Environments*. PhD Thesis, Ecole Nat. Sup. des Mines de Paris, July 2007.

- [18] R. Benenson, S. Petti, T. Fraichard, and M. Parent. Toward urban driverless vehicles. *Int. J. Vehicle Autonomous Systems*, 6(1-2):4–23, 2008.
- [19] P. Garnier. *Contrôle d'exécution réactif de mouvements de véhicules en environnement dynamique structure*. Phd thesis, Inst. Nat. Polytechnique de Grenoble (INPG), December 1995.
- [20] J. Burlet. Déplacements sous incertitudes d'un robot mobile. Master thesis, Inst. Nat. Polytechnique de Grenoble (INPG), June 2004.
- [21] V. Delsart. *Navigation autonome en environnement dynamique : une approche par déformation de trajectoire*. Phd thesis, Université de Grenoble, October 2010.
- [22] L. Martinez. *Safe Navigation for Autonomous Vehicles in Dynamic Environments: an ICS Perspective*. Phd thesis, Université de Grenoble, November 2010.
- [23] Th. Fraichard. A Short Paper about Motion Safety. In *IEEE Int. Conf. on Robotics and Automation*, 2007.
- [24] J. Reif and M. Sharir. Motion planning in the presence of moving obstacles,. In *IEEE Symp. on the Foundations of Computer Science*, Portland, OR (US), October 1985. Published in JACM, 41:4, July 1994, pp. 764–790.
- [25] S. LaValle and J. Kuffner. Randomized kinodynamic planning. In *IEEE Int. Conf. on Robotics and Automation*, Detroit, MI (US), May 1999.
- [26] M. Kalisiak and M. van de Panne. Approximate safety enforcement using computed viability envelopes. In *IEEE Int. Conf. on Robotics and Automation*, Barcelona (ES), April 2004.
- [27] T. Fraichard and H. Asama. Inevitable collision states. a step towards safer robots? *Advanced Robotics*, 18(10):1001–1024, 2004.
- [28] L. Martinez-Gomez and Th. Fraichard. An Efficient and Generic 2D Inevitable Collision State-Checker. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 2008.
- [29] T. Fraichard and J. Kuffner, editors. *Special Issue on Guaranteeing Motion Safety for Robots*, volume 32 of *Autonomous Robots*, 2012.
- [30] Th. Fraichard and H. Asama. Inevitable Collision States. A Step Towards Safer Robots? In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 2003.
- [31] A. Bautin, L. Martinez-Gomez, and Th. Fraichard. Inevitable collision states: a probabilistic perspective. In *IEEE Int. Conf. on Robotics and Automation*, 2010.
- [32] L. Martinez-Gomez and Th. Fraichard. Collision Avoidance in Dynamic Environments: an ICS-Based Solution and Its Comparative Evaluation. In *IEEE Int. Conf. on Robotics and Automation*, 2009.
- [33] R. Parthasarathi and Th. Fraichard. An Inevitable Collision State-Checker for a Car-Like Vehicle. In *IEEE Int. Conf. on Robotics and Automation*, 2007.
- [34] S. Bouraine, T. Fraichard, and H. Salhi. Provably safe navigation for mobile robots with limited field-of-views in dynamic environments. *Autonomous Robots*, 32(3):267–283, 2012.
- [35] L. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. In *Readings in speech recognition*. Morgan Kaufmann, 1990.
- [36] D. Vasquez. Estimation de mouvement des obstacles mobiles: une approche statistique. Master's thesis, Inst. Nat. Polytechnique de Grenoble, Grenoble (FR), September 2003.
- [37] D. Vasquez. *Apprentissage incrémental pour la prédiction des mouvements de piétons et de véhicules*. PhD Thesis, Inst. Nat. Polytechnique de Grenoble, February 2007.

- [38] A. Bruce and G. Gordon. Better motion prediction for people-tracking. In *IEEE Int. Conf. on Robotics and Automation*, New Orleans, LA (US), April 2004.
- [39] A. F. Foka and P. E. Trahanias. Predictive autonomous navigation. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, Lausanne (CH), October 2002.
- [40] M. Bennewitz, W. Burgard, G. Cielniak, and S. Thrun. Learning motion patterns of people for compliant robot motion. *Int. Journal of Robotics Research*, 24(1), 2005.
- [41] J. Jockusch and H. Ritter. An instantaneous topological mapping model for correlated stimuli. In *Proc. International Joint Conference on Neural Networks IJCNN '99*, volume 1, pages 529–534 vol.1, 1999.
- [42] C. Fulgenzi. *Navigation autonome en environnement dynamique utilisant des modèles probabilistes de perception et de prédiction du risque de collision*. PhD thesis, Inst. Nat. Polytechnique de Grenoble, Grenoble (FR), June 2009.
- [43] C. Tay. *Analysis of Dynamic Scenes: Application to Driving Assistance*. PhD thesis, Inst. Nat. Polytechnique de Grenoble, Grenoble (FR), September 2009.
- [44] T. Craesmeyer Bellardi, D. Vasquez Govea, and C. Laugier. Frame rate object extraction from video sequences with self organizing networks and statistical background detection. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, Nice (FR), 2008.
- [45] D. Vasquez, Th. Fraichard, and C. Laugier. Incremental Learning of Statistical Motion Patterns with Growing Hidden Markov Models. In *Int. Symp. of Robotics Research*, 2007.
- [46] D. Vasquez and Th. Fraichard. A Novel Self-Organizing Network to Perform Fast Moving Object Extraction from Video Streams. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 2006.
- [47] D. Vasquez, F. Romanelli, Th. Fraichard, and C. Laugier. Fast Object Extraction from Bayesian Occupancy Grids Using Self Organizing Networks. In *Int. Conf. on Control, Automation, Robotics and Vision*, 2006.
- [48] D. Vasquez, Th. Fraichard, O. Aycard, and C. Laugier. Intentional Motion On-Line Learning and Prediction. In *Int. Conf. on Field and Service Robotics*, 2005.
- [49] C. Laugier, S. Petti, A. D. Vasquez, M. Yguel, Th. Fraichard, and O. Aycard. Steps towards safe navigation in open and dynamic environments. In C. Laugier and R. Chatila, editors, *Autonomous Navigation in Dynamic Environments*, volume 35 of *Springer Tracts in Advanced Robotics Series*, pages 55–82. Springer, 2007.
- [50] A. D. Vasquez, Th. Fraichard, O. Aycard, and C. Laugier. Intentional motion online learning and prediction. In P. Corke and S. Sukkarieh, editors, *Field and Service Robotics*, volume 25 of *Springer Tracts in Advanced Robotics Series*, pages 305–316. Springer, 2006.
- [51] D. Vasquez, T. Fraichard, and C. Laugier. Growing hidden markov models: a tool for incremental learning and prediction of motion. *Int. J. Robotics Research*, 28(11-12):1486–1506, November 2009.
- [52] D. Vasquez, T. Fraichard, and C. Laugier. Incremental learning of statistical motion patterns with growing hidden markov models. *IEEE Trans. Intelligent Transportation Systems*, 10(3):403–416, September 2009.
- [53] D. Vasquez. *Incremental Learning for Motion Prediction of Pedestrians and Vehicles*, volume 64 of *Springer Tracts in Advanced Robotics*. Springer, 2010.
- [54] J.-P. Laumond. Feasible trajectories for mobile robots with kinematic and environment constraints. In *Proc. Int. Conf. Intelligent Autonomous Systems*, Amsterdam (NL), December 1986.
- [55] J.-P. Laumond, P. E. Jacobs, M. Taix, and R. M. Murray. A motion planner for non-holonomic mobile robots. *IEEE Trans. Robotics and Automation*, 10(5), October 1994.

- [56] E. Mazer, J.-M. Ahuactzin, and P. Bessière. The Ariadne's Clew algorithm. *Journ. of Artificial Intelligence Research*, 9, July-December 1998.
- [57] A. Scheuer. *Planification de chemins à courbure continue pour robot mobile non-holonyme*. PhD Thesis, Inst. Nat. Polytechnique de Grenoble, Grenoble (FR), January 1998.
- [58] Th. Fraichard, A. Scheuer, and R. Desvigne. From Reeds And Shepp's to Continuous-Curvature Paths. In *IEEE Int. Conf. on Advanced Robotics*, 1999.
- [59] T. Fraichard and A. Scheuer. From reeds and shepp's to continuous-curvature paths. *IEEE Trans. Robotics*, 20(6):1025–1035, December 2004.
- [60] L. E. Dubins. On curves of minimal length with a constraint on average curvature, and with prescribed initial and terminal positions and tangents. *American Journal of Mathematics*, 79, 1957.
- [61] A. Sanchez Lopez. *Contribution à la planification de mouvements en robotique: approches probabilistes et déterministes*. PhD Thesis, Université Montpellier II, Montpellier (FR), July 2003.
- [62] J. Peng and S. Akella. Coordinating multiple robots with kinodynamic constraints along specified paths. *Int. Journal of Robotics Research*, 24(4), April 2005.
- [63] Th. Fraichard and J.-M. Ahuactzin. Smooth Path Planning for Cars. In *IEEE Int. Conf. on Robotics and Automation*, 2001.
- [64] A. Scheuer and Th. Fraichard. Continuous-Curvature Path Planning for Car-Like Vehicles. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 1997.
- [65] A. Scheuer and Th. Fraichard. Collision-Free and Continuous-Curvature Path Planning for Car-Like Robots. In *IEEE Int. Conf. on Robotics and Automation*, 1997.
- [66] A. Scheuer and Th. Fraichard. Planning Continuous-Curvature Paths for Car-Like Robots. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 1996.
- [67] C. Coué. *Modèle bayésien pour l'analyse multimodale d'environnements dynamiques et encombrés: application à l'assistance à la conduite automobile en milieu urbain*. PhD Thesis, Inst. Nat. Polytechnique de Grenoble, December 2003.
- [68] D. Hähnel, D. Schulz, and W. Burgard. Mobile robot mapping in populated environments. *Advanced Robotics*, 17(7), 2003.
- [69] C.-C. Wang. *Simultaneous Localization, Mapping and Moving Object Tracking*. PhD thesis, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, April 2004.
- [70] D. Wolf and G. Sukhatme. Mobile robot simultaneous localization and mapping in dynamic environments. *Autonomous Robots*, 19, 2005.
- [71] M. Buehler, K. Lagnemma, and S. Singh, editors. *Journal of Field Robotics*, volume 25(8). Wiley, August 2008. Special Issue on the 2007 DARPA Urban Challenge, Part I.
- [72] M. Buehler, K. Lagnemma, and S. Singh, editors. *Journal of Field Robotics*, volume 25(9). Wiley, September 2008. Special Issue on the 2007 DARPA Urban Challenge, Part II.
- [73] M. Buehler, K. Lagnemma, and S. Singh, editors. *Journal of Field Robotics*, volume 25(10). Wiley, October 2008. Special Issue on the 2007 DARPA Urban Challenge, Part III.
- [74] C. Coue, C. Pradalier, C. Laugier, T. Fraichard, and P. Bessiere. Bayesian occupancy filtering for multi-target tracking: an automotive application. *Int. J. Robotics Research*, 25(1):19–30, January 2006.
- [75] C. Coue, C. Pradalier, C. Laugier, and Th. Fraichard. Bayesian programming for multi-target tracking: an automotive application. In *Int. Conf. on Field and Service Robotics*, 2003.

- [76] C. Coue, Th. Fraichard, P. Bessiere, and E. Mazer. Using bayesian programming for multi-sensor multi-target tracking in automotive applications. In *IEEE Int. Conf. on Robotics and Automation*, 2003.
- [77] C. Coue, Th. Fraichard, P. Bessiere, and E. Mazer. Multi-sensor data fusion using bayesian programming: an automotive application. In *IEEE-RSJ Int. Conf. on Intelligent Robots and Systems*, 2002.
- [78] C. Coue, Th. Fraichard, P. Bessiere, and E. Mazer. Using bayesian programming for multi-sensor data fusion in automotive applications. In *IEEE Intelligent Vehicle Symp.*, 2002.
- [79] M. Tay, K. Mekhnacha, M. Yguel, C. Coue, C. Pradalier, C. Laugier, Th. Fraichard, and P. Bessiere. The bayesian occupation filter. In P. Bessiere, C. Laugier, and R. Siegwart, editors, *Probabilistic Reasoning and Decision Making in Sensory-Motor Systems*, volume 46 of *Springer Tracts in Advanced Robotics Series*, pages 77–98. Springer, 2008.
- [80] O. Lefebvre, F. Lamiriaux, C. Pradalier, and Th. Fraichard. Obstacles Avoidance for Car-Like Robots. Integration and Experimentation on Two Robots. In *IEEE Int. Conf. on Robotics and Automation*, 2004.
- [81] E. Boniface. Gestion d’une plate-forme de vidéo-surveillance à usage robotique: modélisation d’un environnement dynamique. Mémoire de fin d’études, Conservatoire Nat. des Arts et Métiers, Grenoble (FR), March 2006.
- [82] F. Hélin. Développement de la plate-forme expérimentale parkview pour la reconstruction de l’environnement dynamique. Mémoire de fin d’études, Conservatoire Nat. des Arts et Métiers, Grenoble (FR), July 2003.