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Local Dynamic Path Planning for an Autonomous Forklift in Human Environment

Unclassified Report

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1 Introduction

This document is meant to describe the work done until now as well as the partial results and the perspectives for my final year internship as an engineering student at ENSTA ParisTech and UPMC - Paris VI.

The first two months of this internship took place at the "Unité Informatique et Ingénierie des Systèmes" at ENSTA under the supervision of David Filliat. After that, from May until the end of August I have been working at CEA LIST Digiteo Moulon under the supervision of Eric Lucet.

1.1 Internship context

The work developed during this internship falls within the context of an applied research project on automation of a forklift truck fleet for the effective supply of assembly lines.

Thus, the mobile robots have to be able to evolve in an environment that is partially known and shared with humans. At the same time they have to be efficient with respect to time for completing its tasks while preserving the workers' safety.

1.2 Objectives

The main objective of this internship is to implement, test, evaluate and improve an optimal path planning algorithm presented in details in [Defoort, 2007] with respect to its applicability to a scenario where autonomous forklift trucks and humans share the same environment.

This planning algorithm consists in planning the mobile robot's path by solving a direct trajectory optimization problem [Betts, 1998] using B-splines for representing the system flat output [Milam, 2003]. As stated in [Defoort, 2007] compared with other solutions this approach presents good advantages for multi-robots systems evolving in an uncertain environment with static obstacles. For instance, analytic methods are inapplicable for nonholonomic systems in presence of obstacles [Schwartz and Sharir, 1988]. Cell decomposition methods [Latombe, 2012] have the downside of requiring an *a priori* space modeling. The dynamic window approach [Fox et al., 1997] is not flexible enough to be extended to a multi-robot system.

The two main challenges that may be confronted during this work are how to guarantee real-time performance for our specific application and how to generalize the algorithm in order to account for dynamic obstacles (including humans).

2 Initial achievements

During the first two months of this work we focused in understanding and reproducing the trajectory generation algorithm presented in [Defoort, 2007] going from a single robot global planning method to a multi-robot local real-time planning. During the third month we focused in the analysis of the impact of different parameters in the method performance and feasibility.

2.1 Nonlinear programming problem (NLP)

Firstly we studied how the path planning problem could be translated into a nonlinear programming problem by intelligently using the mobile robot's model flatness property and representing the trajectory by B-splines.

2.1.1 Problem Formulation

Let us briefly and without mathematical rigor present how the problem of finding a collision-free, optimized path for a mobile robot represented by a unicycle model can be written.

The equation 2.1 represents the unicycle kinematic model. Thanks to the flatness property it is possible to be exclusively interested in planning a trajectory for the flat output variable z where $z = [x,\ y]^T$.

$$\begin{gathered}\dot{q} = \mathrm{f}(q,u) \Rightarrow \\ \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v\cos(\theta) \\ v\sin(\theta) \\ w \end{bmatrix}\end{gathered} \tag{2.1}$$

The equations 2.2, 2.3 show how the state variables and control variables can be calculated from the flat output and its first l^{th} derivatives. Whenever we need to retrieve the fundamental variables we can by means of these equations.

$$\begin{gathered}\varphi_1(z(t_k),\ldots,z^{(l-1)}(t_k)) = \\ \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ \arctan(\dot{z}_2/\dot{z}_1) \end{bmatrix}\end{gathered} \tag{2.2}$$

$$\begin{gathered}\varphi_2(z(t_k),\ldots,z^{(l)}(t_k)) = \\ \begin{bmatrix} v \\ \omega \end{bmatrix} = \begin{bmatrix} \sqrt{\dot{z}_1^2+\dot{z}_2^2} \\ \dfrac{\dot{z}_1\ddot{z}_2 - \dot{z}_2\ddot{z}_1}{\dot{z}_1^2+\dot{z}_2^2} \end{bmatrix}\end{gathered} \tag{2.3}$$

Now let us write the NPL problem that minimizes the square of the time spend (2.4) to go from a $q_{initial}$ pose at a $u_{initial}$ velocity to a q_{final} pose at a u_{final} velocity, avoiding M static obstacles represented by circles with radius r_m [1], having velocities in an admissible velocity set denoted by $\mathcal{U}$.

1. the own robot geometry is here represented by a circle of radius ρ

$$\min_{(t_{final}, C_0, \ldots, C_{d+n_{knot}-2})} J = (t_{final} - t_{initial})^2 \tag{2.4}$$

under the following constraints $\forall k \in \{0, \ldots, N_s - 1\}$ and $\forall m \in 0, \ldots, M-1$:

$$\begin{cases} \varphi_1(z(t_{initial}), \ldots, z^{(l-1)}(t_{initial})) & = & q_{initial} \\ \varphi_1(z(t_{final}), \ldots, z^{(l-1)}(t_{final})) & = & q_{final} \\ \varphi_2(z(t_{initial}), \ldots, z^{(l)}(t_{initial})) & = & u_{initial} \\ \varphi_2(z(t_{final}), \ldots, z^{(l)}(t_{final})) & = & u_{final} \\ \varphi_2(z(t_k), \ldots, z^{(l)}(t_k)) & \in & \mathcal{U} \\ d_{O_m}(t_k) & \geq & \rho + r_m, \quad \forall O_m \in \mathcal{Q}_{occupied} \end{cases} \tag{2.5}$$

2.1.2 Implementation of the solution

Once we were able to write the problem as above the subsequent step was to implement this planning method using some programming language. We kept in mind that a high level language provided with some NLP solver package would be preferable.

We decided to use Python language and the Scipy package. Within the Scipy module many minimization methods can be found. For this specific optimization problem, only the method SLSPQ was appropriate. It was the only one to handle constrained minimization where the constraints could be equations as well as inequations.

Since the SLSPQ is a local optimization method the first guess used for initializing the solver had an impact on the time of convergence as well as on the found solution. A bad first guess can prevent the solver for converging at all, as shown in the Figure 1.

Besides the influence of a bad initialization we notice another problem that could cause the Scipy implementation of the SLSQP solver not to converge. A too big cost value for the objective function (e.g. values greater than 10^6) could also prevent the convergence of the solver.

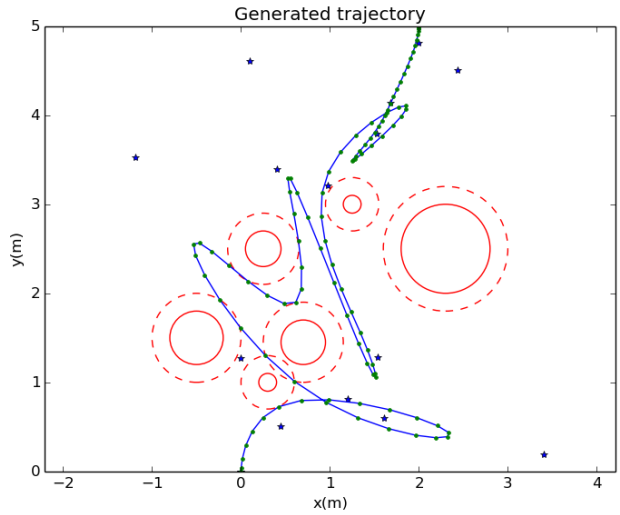


Figure 1 – Path resulting from a bad initialization

An initialization algorithm was then proposed along some changes in the objective function evaluation so better solutions could be achieved quicker.

The initialization algorithm is a simple one that interactively changes the positions of the B-splines control points in order to prevent the initial trajectory guess to pass between two obstacles that are too close together (distance inter-obstacle smaller than the robot's diameter).

2.2 Evolving from the previous NLP to the sliding window multi-robot decentralized approach

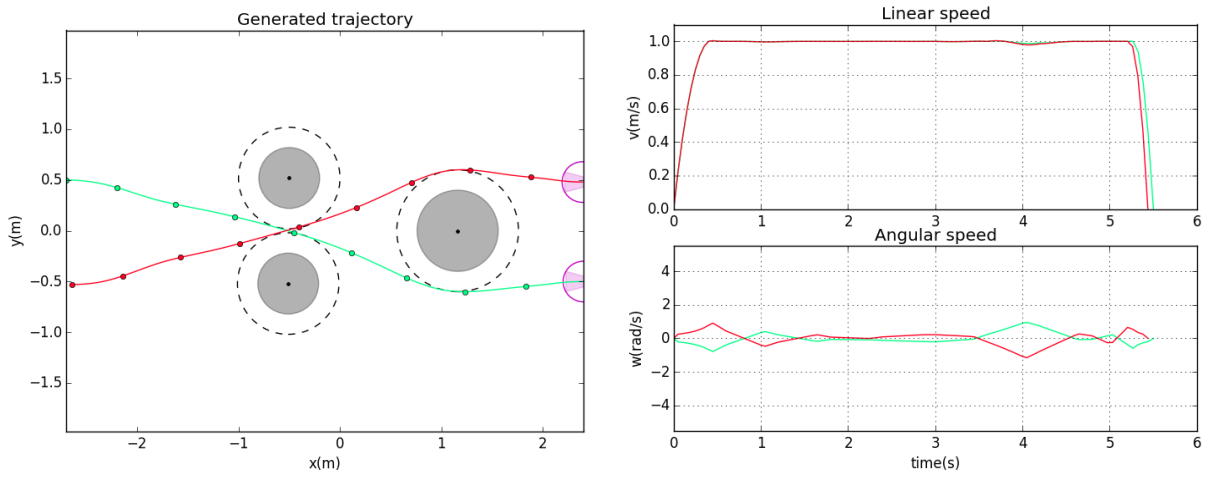
Solving the problem as stated in the previous subsection is only worth considering as a base initial solution to our problem.

Following the work done in [Defoort, 2007] we built over the first implementation so to have a strongly decentralized planner for multi-robot fleet that is collision-free with respect to the robots in the fleet as well as to static obstacles as before. This new approach was suitable for real-time implementation as well. We chose a strongly decentralized approach over a centralized one in order to have no central supervisor and to keep the computation complexity of solving the trajectory optimization problem close to the one in a single robot system.

Using a sliding window the new planner produced a "per robot" intended trajectory meant to be valid within a planning horizon. This trajectory is locally optimal with respect to a new objective function and collision-free with respected to the static obstacles.

The presence of other robots is taken into account in a second stage: the planned trajectory is updated after the robots involved in a possible conflict [2] exchange their intended trajectories. This update consists in solving a second NPL where the intended trajectories of other robots are take into account.

Figures 2 and 3 show two solutions for the same multi-robot path planning problem. In Figure 2 conflicts are not handled while in Figure 3 we notice changes on the path and velocities that indicate the conflict avoidance.

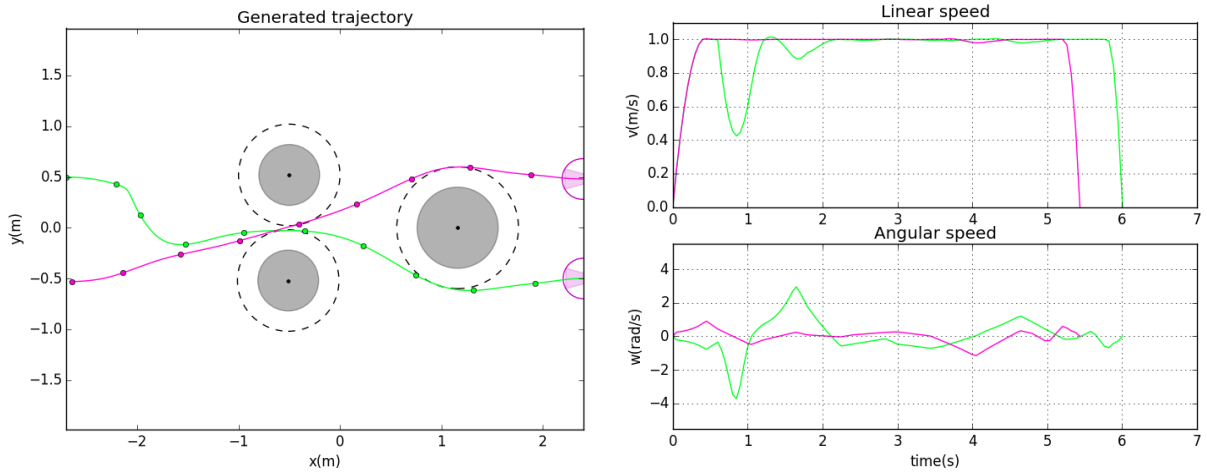


(a) Generated paths

(b) Velocities

Figure 2 – Multi-robot path generation without conflict handling

2. The word conflict is used to account for two different situations: collisions and lost of communications between the robots in the feet.



(a) Generated paths (b) Velocities

Figure 3 – Multi-robot path generation with conflict handling

2.3 Analysis of the parameters impact on real-time feasibility and solution adequacy

The performance and solution quality of the motion planning algorithm previously presented depends on several parameters. These parameters can be split into two groups. The **algorithm related** parameters and the **optimization solver related** ones. Among the former group, the most important ones are:

- The number of sample for time discretization (N_s);
- The number of internal knots for the B-splines curves (n_{knots});
- The planning horizon for the sliding window (T_p);
- The computation horizon (T_c).

The latter kind depends on the optimization solver adopted. However, since most of them are iterative methods, it is common to have at least the two following parameters:

- Maximum number of iterations;
- Stop condition.

This high number of parameters having influence on the solution and/or on the time for finding a solution makes the search for a satisfactory set of parameters' values a laborious task.

We attempted nevertheless to extract some quantitative knowledge about this influence through several simulations run with different parameters configurations. The main objective being to support the feasibility of a real-time motion planner based on this algorithm.

To give an overview of the simulations performed we present one of the many data used in our analysis in Figure 5 and Figure 4. Figure 4 shows the solution (path and velocities) for one of the scenarios that were simulated for a given set of parameters listed in the table 1. Keeping the scenario and varying the parameters we were able to plot the charts on Figure 5. We can notice an impact of the number of samples (N_s) and number of non-null internal knots (n_{knots}) on the *maximum computation time*$/T_c$ ratio. The greater the n_{knots} or the N_s the greater is the *maximum computation time*$/T_c$. This behavior is the one expected since the number of constraints and the number of arguments for the cost function to be minimized depend on these two parameters respectively. Notice that

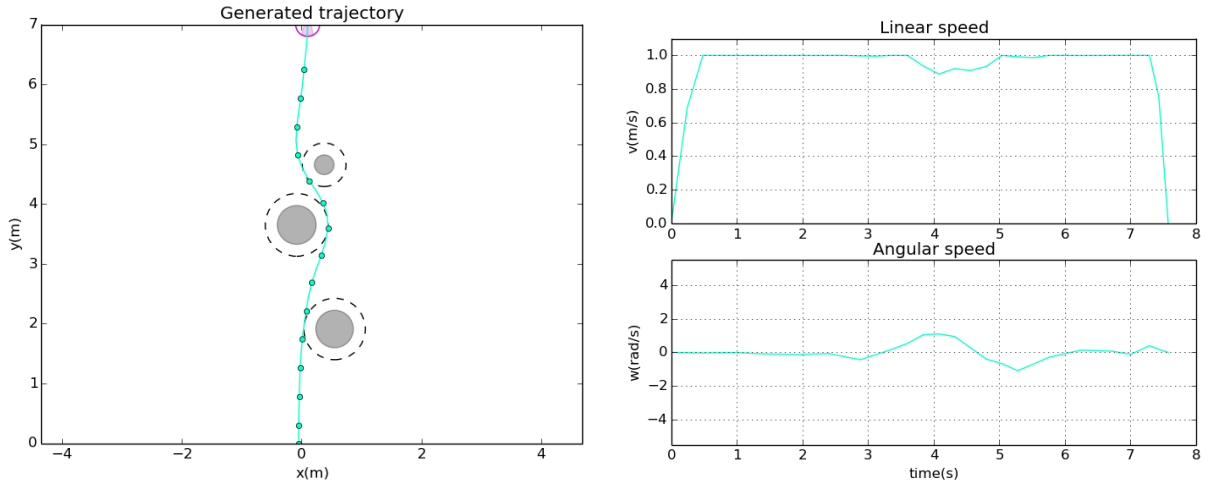
the *maximum computation time*/T_c ratio has to be inferior to one so real-time planning is possible.

We were also able to characterize the influence of the number of obstacles seen at once on the computation time and path quality. As expected the computation time increases with the number of obstacles seen at once.

Finally we proposed some metric to characterize the adequacy of a found solution based on the total time spend going from the initial to the final pose and on the robot to the obstacles distance.

Table 1 – Simulation main parameters

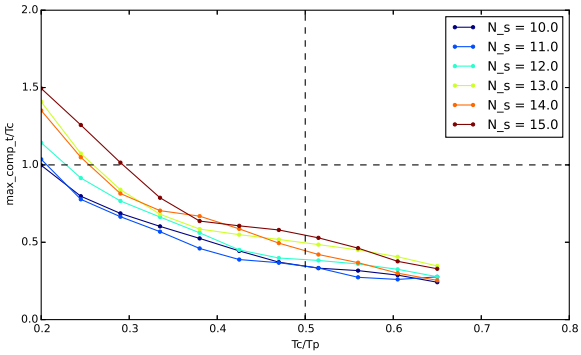
T_p	2.40 s
T_c	0.48 s
N_s	11
n_{knots}	4
v_{max}	1.00 m/s
ω_{max}	5.00 rad/s
q_{inital}	$[-0.05\ 0.00\ \pi/2]^T$
q_{final}	$[0.10\ 7.00\ \pi/2]^T$
u_{final}	$[0.00\ 0.00]^T$
u_{final}	$[0.00\ 0.00]^T$
O_0	[0.55 1.91 0.31]
O_1	[−0.08 3.65 0.32]
O_2	[0.38 4.65 0.16]



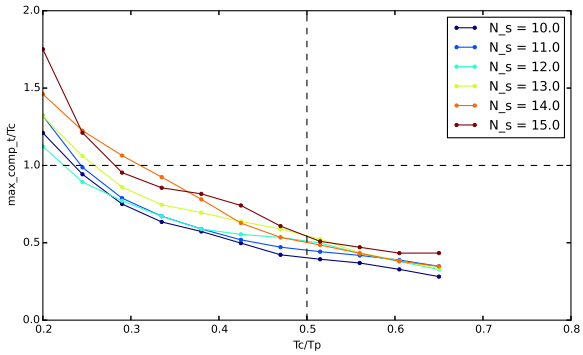
(a) Generated path

(b) Velocities

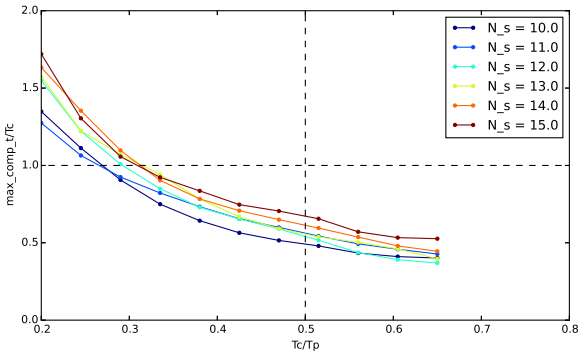
Figure 4 – Three obstacles scenario simulation example where the *maximum computation time* was about 84% of T_c and the mission total time equals to 7.57 s.



(a) Four internal knots. Average variance between lines is 1.047×10^{-2}



(b) Five internal knots. Average variance between lines is 0.972×10^{-2}



(c) Six internal knots. Average variance between lines is 0.587×10^{-2}

Figure 5 – Three obstacles scenario

2.4 From Python to XDE simulator

XDE is a physics simulation software environment fully developed by CEA-LIST that can handle a variety of physical aspects such as deformable bodies, multibody systems with kinematic constraints and contacts, and fluids. Its utilization presents though some rough edges and a steep learning curve.

During the third month and beginning of the forth while producing the analysis referenced by the latest subsection we begin porting the implementation done in python to the XDE environment.

The objective is to get much closer to a real physical system being able to implement dynamic behavior in the simulated environment which was previously neglected.

An overview of the simulator visual environment showing the unicycle mobile robot used for implementing the algorithm can be seen in Figure 6.

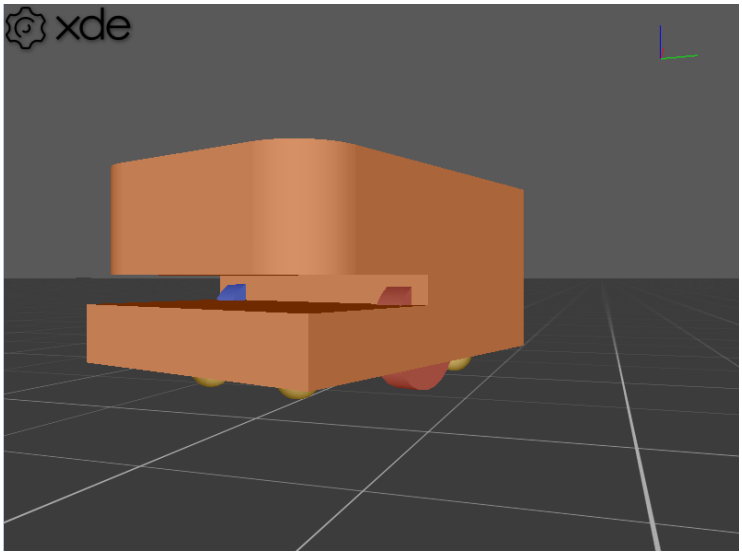


Figure 6 – XDE - unicycle mobile robot application.

3 Discussion

We implemented and did some minor improvements on the solution proposed by [Defoort, 2007] and we gather a good understanding of the impact of the algorithm's parameters in the computation cost and in the quality of the solution.

The main advantages of the studied approach are:

- It handles path planning for multi-robot systems avoiding collisions as well as lost of communication conflicts without greatly increasing the computation complexity.
- It allows collision avoidance and prevents lost of communication between robots in the fleet without greatly increasing the computation complexity.
- It can respect real-time constraints for a multi-robot system evolving in a unknown environment where a certain amount of static obstacles are present.
- It provides a near-optimal solution.

The main drawbacks are listed below:

- Difficulty in choosing a set of parameters (algorithm and numerical solver related) well adapted to a given scenario especially in order to have real-time performance.
- Not adapted to the presence of dynamic obstacles as it is.

Regarding the first drawback listed above we were able to identify the parameters that have a bigger influence on the solution adequacy and computation time. The number of samples (N_s) is the parameter that greatly impacts the computation time followed by the number of obstacles detected at once by the robot (defined by the detection radius and the obstacles positioning with respect to the robot throughout time). Furthermore, the solution adequacy depends highly on the N_s/T_p ratio and on the number of internal knots of the B-spline representation n_{knots}.

As expected, the cost for better solution adequacy is a higher computation time. The key to improve this approach is probably in using a better initial path (possibly in combination with other approaches) before starting solving the NLPs involved in the algorithm.

4 Perspectives

During the months to come we intend to finish the implementation of the C++ code in the XDE dynamic simulator and extend the analysis about real-time performance and solution adequacy based on this new implementation. Also, we plan to compare this approach against other path planning methods with similar characteristics, e.g. the solution presented by [Kelly and Nagy, 2003]. Then, we shall extend the current approach so it can address dynamic obstacles.

Finally, we plan to write a paper summarizing the conclusions gathered during my internship for submitting to the International Workshop on On-line Decision-Making in Multi-Robot Coordination [Workshop, 2015].

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