PROJET DE FIN D'ÉTUDES (PFE)

INGÉNIERIE SYSTÈME : ROBOTIQUE ET SYSTÈMES EMBARQUÉS

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Local Dynamic Motion Planning for an Autonomous Forklift in Human Environment

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Unclassified Report

Can be made public on the internet

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Promotion 2014

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Acknowledgements

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Résumé

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Abstract

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Work Descritpion

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Part II

Internship Contribution

Chapter 2

Global Near-optimal Solution for Path Planning

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2.1 Description of the Problem

Chapter 3

Algorithmic Approach

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3.1 Optimizers

There is a variety of numerical optimization packages implemented in many different programming languages available for solving optimization problems [10]. Each of them may have their own way of defining the optimization problem and may or may not support specific kinds of constraints (equations, inequations or boundaries).

For the initial implementation written in python two packages stood out as good, easy-to-use options for solving the constrained optimization problem that models the planning motion task.

Scipy is a vast open-source scientific package based on python that happens to have a minimization module. Within this 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.

pyOpt is a much smaller ecosystem than Scipy that is specialized in optimization. It gathers many different numerical optimization algorithms some of them free and some licensed. Again, among all of them there were only a few suitable for this problem which were also free: SLSQP (same as the one implemented within Sicpy), PSQP and ALGENCAN.

SLSQP and PSQP are both SQP (for sequential quadratic programming) methods. A SQP method attempts to solve a nonlinearly constrained optimization problem where the object function and the constraints are twice continuously differentiable. It does so by modeling the object function ($\min f(x)$) at the current iterate x_k by a quadratic programming subproblem and using the minimizer of this subproblem to define a new iterate x_{k+1} [9].

The ALGENCAN method

describe algecan

$$\min_{(t_{final}, C_0, \dots, C_{d+n_{knot}-2})} J = (t_{final} - t_{initial})^2 \tag{3.1.1}$$

under the following constraints $\forall k \in \{0, \dots, N_s - 1\}$:

$$\begin{cases} \varphi_1(z(t_{initial}), \dots, z^{(l-1)}(t_{initial})) & = & q_{initial} \\ \varphi_1(z(t_{final}), \dots, z^{(l-1)}(t_{final})) & = & q_{final} \\ \varphi_2(z(t_{initial}), \dots, z^{(l)}(t_{initial})) & = & u_{initial} \\ \varphi_2(z(t_{final}), \dots, z^{(l)}(t_{final})) & = & u_{final} \\ \varphi_2(z(t_k), \dots, z^{(l)}(t_k)) & \in & \mathcal{U} \\ d_{O_m}(t_k) & \geq & \rho + r_m, \quad \forall O_m \in \mathcal{Q}_{occupied} \end{cases} \tag{3.1.2}$$

— Problem with discretization

Try adding CONSTRAINTS related to max acceleration (DONE)
For that we have to increase the maximum derivative order of the flat output needed so we calculate $[\dot{v}\ \dot{\omega}]$ building a φ_3 function
Also, the constraints to be added:

$$\varphi_3(z(t_k), \ldots, z^{(l)}(t_k)) \in \mathcal{A}$$

where $\mathcal{A}$ is the set of admissible acceleration values.
The function φ_3 is as follows:

$$\begin{aligned}&\varphi_3(z(t_k), \ldots, z^{(3)}(t_k)) = \\ &= \begin{bmatrix} \dot{v} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial t}\|\dot{z}\| \\ \frac{\partial}{\partial t}\frac{(\dot{z}_1\ddot{z}_2 - \dot{z}_2\ddot{z}_1)}{\|\dot{z}\|^2} \end{bmatrix} = \begin{bmatrix} \frac{\dot{z}_1\ddot{z}_1 + \dot{z}_2\ddot{z}_2}{\|\dot{z}\|} \\ \frac{(\ddot{z}_1\ddot{z}_2 + z_2^{(3)}\dot{z}_1 - (\ddot{z}_2\ddot{z}_1 + z_1^{(3)}\dot{z}_2))\|\dot{z}\|^2 - 2(\dot{z}_1\ddot{z}_2 - \dot{z}_2\ddot{z}_1)\|\dot{z}\|\dot{v}}{\|\dot{z}\|^4} \end{bmatrix}\end{aligned}$$

— Remake code using good objected oriented structure. It will be good for C++ part (DONE)

ONLINE T_c and T_p (planning horizon) "given" (arbitrary).

$$\tau_k = t_{initial} + kT_c \quad k \in \mathbb{N}$$

Arbitrary detection radius for the robot sensors. Only if the obstacle characteristic position is inside the detection zone the obstacle is considered detected. Using $2m$.

Evaluate for each time interval $[\tau_{k-1}, \tau_k)(k \in \mathbb{N})$ the trajectory beginning at τ_k until $\tau_k + T_p$:

$$\min_{(C_{(0,\tau_k)}, \ldots, C_{(d+n_{knot}-2,\tau_k)})} J_{\tau_k} = \|\varphi_1(z(\tau_k + T_p, \tau_k), \ldots, z^{(l-1)}(\tau_k + T_p, \tau_k)) - q_{final}\|^2 \tag{3.1.3}$$

under the following constraints $\forall t \in [\tau_k, \tau_k + T_p]$:

$$\begin{cases} \varphi_1(z(\tau_k, \tau_k), \ldots, z^{(l-1)}(\tau_k, \tau_k)) & = & q_{ref}(\tau_k, \tau_{k-1}) \\ \varphi_2(z(\tau_k, \tau_k), \ldots, z^{(l)}(\tau_k, \tau_k)) & = & u_{ref}(\tau_k, \tau_{k-1}) \\ \varphi_2(z(t, \tau_k), \ldots, z^{(l)}(t, \tau_k)) & \in & \mathcal{U} \\ d_{O_m}(t, \tau_k) & \geq & \rho + r_m, \quad \forall O_m \in \mathcal{O}(\tau_k) \end{cases} \tag{3.1.4}$$

The period $[\tau_{-1}, \tau_0)$ is what is called by Defoort "the initialization phase" which considers:

$$q_{ref}(\tau_0, \tau_{-1}) = q_{initial}$$

$$u_{ref}(\tau_0, \tau_{-1}) = u_{initial}$$

without no more further changes to the expressions above.

Practical stuff for implementation $q \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$. N_s number of time steps used when computing the problem.

Number of equations: $n + m$

Number of inequations (function of τ_k): $N_s(m + \mathrm{card}(\mathcal{O}(\tau_k)))$

dependencies: sudo apt-get install python python-dev libatlas-base-dev gcc gfortran g++

get source: https://pypi.python.org/pypi/scipy

sudo python setup.py install

3.2 The mobile robot

For representing the mobile robot geometry in the planning plane a bounding circle was chosen.

3.2.1 Unicycle kinetic model

3.2.2 Flat output formulation

3.3 The obstacles

Two different representations of an obstacle are supported. Obstacles can be seen as circles or convex polygons.

Representing an obstacle as a circle is probably the most simple way of doing so and has great advantages when calculating point-to-obstacle distance compared to other representations.

Nevertheless, obstacles such as walls, boxes and shelves cannot be satisfactorily represented by circles. Thus the need of a polygon representation.

3.3.1 Robot-to-obstacle distance calculation for the convex polygon representation

As sad before the robot's geometric form is represented by a circle. When calculating the robot-to-obstacle distance this simplified representation is quite useful. The first approach to calculate the distance between a point and an obstacle represented by a convex polygon was to separate the problem in three cases with a different expression for the distance computation each. We see in the figure 3.1 that the points A, B and C are placed in three different regions with respect to the obstacle. A is "between" the two lines ($r_{0,1}$ and $r_{0,3}$) that pass through the vertex 0 and are orthogonal to the the two adjacent edges. B is "between" the edge s_3, and the orthogonal lines $r_{0,3}$ and $r_{3,2}$. C is in the interior of the obstacle representation, i.e., surrounded by the four edges.

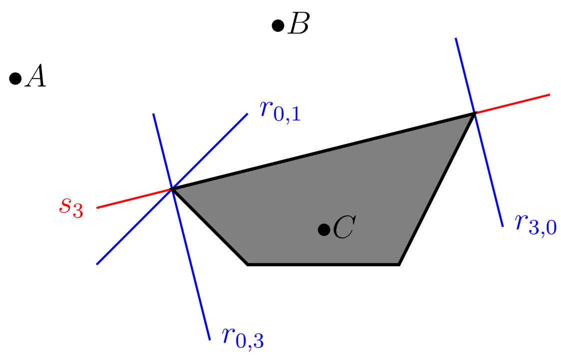


Figure 3.1 – Voronoi regions used for case differentiation.

These cases make use of Voronoi regions [4]. Based on the three types of regions (here we consider the interior of the polygon as a third one) a case differentiation is made and, depending on the case, equations are solved.

It is easy to see that the computation of the point-to-obstacle distance for A is a simple point-to-point distance using the appropriate vertex. For B a point-to-line distance equation can be used. Finally, since C is in the interior of the polygon the penetration distance is calculated. It is considered as the shortest of the four distances from the point C to the four edges multiplied by -1 (so, once more, point-to-line distance).

Of course that the performance of this approach is "number of edges"-dependent and present fast results only or polygons with few edges (less than 10).

10 was arbitrary, improve this finding a meaningful value or delete it

An important remark though is that for a given planning horizon N_s point-to-obstacle distances have to be calculated. Intuitively we can say that there is a high probability that most of the N_s points are inside the same region defined by theirs relative positions to the obstacle. Besides, the probability of finding points inside regions that are "far" from the already occupied zones is smaller. This heuristic can be used to speed up the planning process by having a smarter initialization of point-to-obstacle distance computation when using a convex polygon representation.

Finally, when dealing with more complex obstacles representations and/or with a more complex representation of the mobile robot geometry the Enhanced Gilbert-Johnson-Keerthi distance algorithm [4] is a more suitable and efficient approach.

some code is available on the internet, Google code written in D language and/or the other one on stackoverflow, see bookmarks

3.4 Analysis of real-time planning feasibility and total time performance

The performance of the motion planning algorithm previously presented depends on several parameters. For starters 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}), and the planning and computation time horizons (T_p and T_c respectively). The latter kind depends on the optimization solver adopted but since most of them are iterative methods is common to have at least a "maximum number of iterations" and a "stop condition" parameters.

The task of searching for a satisfactory set of parameters' values with regard to a performance metric (e.g. total time to complete the mission) is quite laborious.

We attempt nevertheless to extract some quantitative knowledge about how these parameters impact the generated solution based on several simulations run with different parameters configurations. The main objective here is to be able to support the feasibility of a real-time motion planner based on this algorithm.

Aiming for a scenario invariant understanding of the impact of these parameters three different scenarios were studied. A first scenario where the robot did not had to avoid any obstacle to complete its mission, a second one where three round obstacles were randomly generated in a region where the robot was probably going to pass through and a third similar to the second only with six instead of three obstacles.

In the other hand, to reduce the problem's size, a unique optimization solver with fixed parameters was used for all simulations. The used parameters can be seen in table 3.1. Different maximum numbers of iterations are used for different stages of the planning process. The subscribed words *first*, *inter* and *last* indicate that the respective maximum numbers of iteration are used for the first optimization problem solving, for all intermediaries ones and for the last one.

talk about accuracy

Table 3.1 – Optimization solver parameters

Optimization solver type	SLSQP
$MAXIT_{first}$	40
$MAXIT_{inter}$	15
$MAXIT_{last}$	20
accuracy	10^{-3}

Real-time feasibility in this context can be considered as having the *maximum computational time* spend for planning the path sections [1] less than or equal to the computation horizon (T_c) . Here though we are only interest in understanding the variation of *maximum computational time*$/T_c$ with changes on T_c, T_p, N_s, N_{knots}.

Another natural performance metric that should be kept in mind is the total time spend to complete the mission (going from the initial configuration to the final).

After this analysis we shall be able to identify sets of parameters' values that minimize the total time spend to complete the mission, respecting the problem constraints and minimizing the *maximum computational time*$/T_c$ ratio.

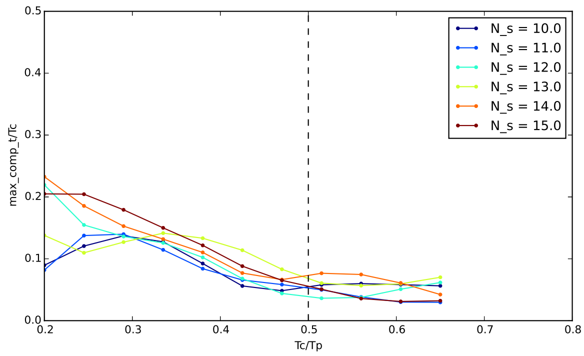
3.4.1 Computation time analysis

No obstacles scenario

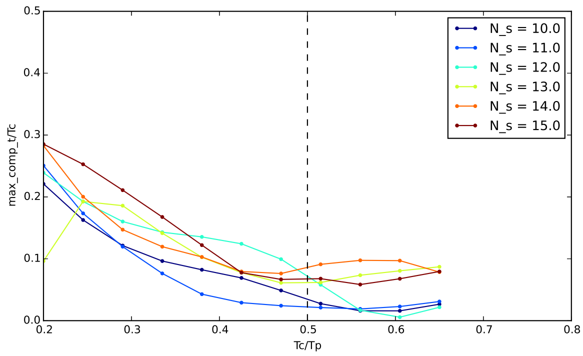
The images in the figure 3.2 try to make prominent the effect of changes in the in the number of samples (N_s) and number of internal knots (N_{knots}). In the ordinate axis we have the *maximum computational time*$/T_c$ ratio and in the abscissa we have the T_c/T_p. For each N_s we took the average of the *maximum computational time*$/T_c$ ratio for a give T_c/T_p among different T_p values in order to be T_p invariant.

1. All computational times spend for planning all sections are considered for finding the maximum value but the first one

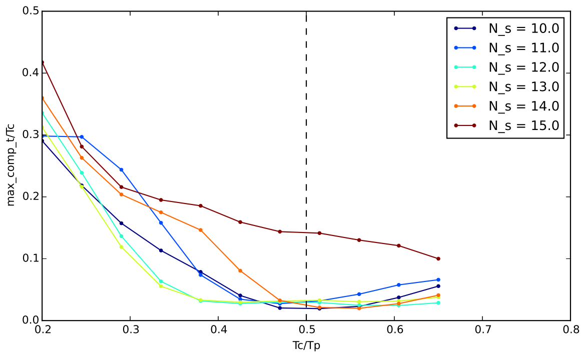
We can see that for a "no obstacles" scenario the overall performance with respect to the *maximum computational time*$/T_c$ ratio is only slightly impacted by variations in the number of samples (N_s) and in the number of internal knots (N_{knots}). Within a given image the lines are close together showing that variations in N_s have weak impact. In addition, comparing the three images (3.2a, 3.2b, 3.2c) we see that variations in the N_{knots} have also a weak influence.



(a) Four internal knots. Average variance between lines is 0.062×10^{-2}



(b) Five internal knots. Average variance between lines is 0.115×10^{-2}



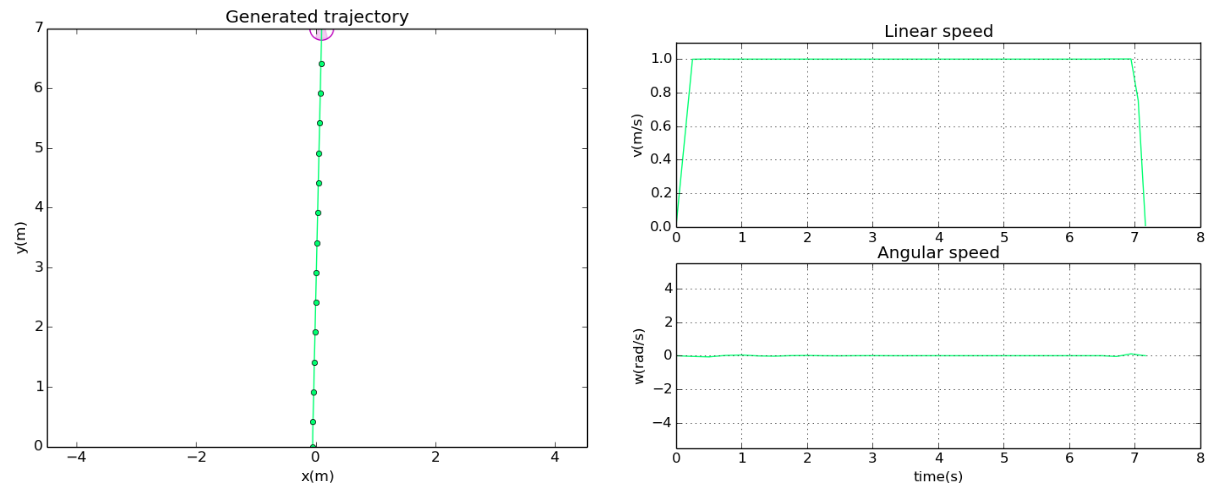
(c) Six internal knots. Average variance between lines is 0.182×10^{-2}

Figure 3.2 – Zero obstacles scenario.

For the sake of an example we present a simulation result in the figure 3.3 run with the parameters presented in the table 3.2 for a "no obstacles" scenario.

Table 3.2 – Motion planner main parameters

T_p	2.00 s
T_c	0.40 s
N_s	9
N_{knots}	5
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}	$[0.00\ 0.00]^T$



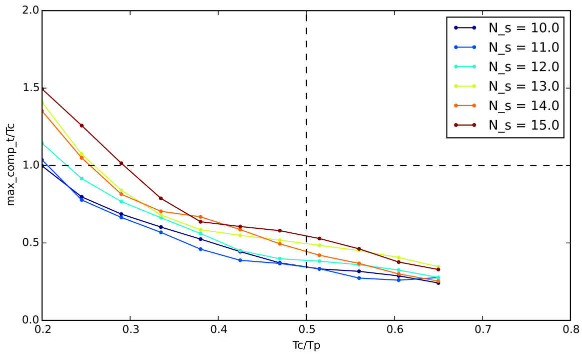
(a) Robot's path.

(b) Robot's input.

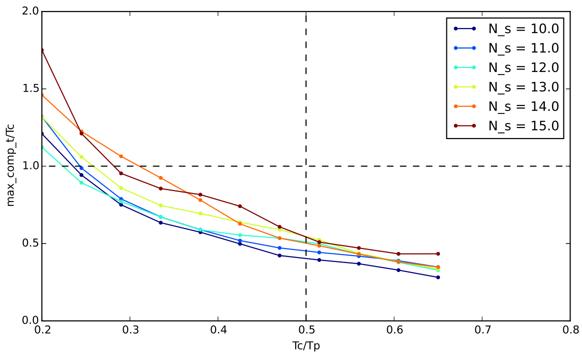
Figure 3.3 – No obstacle scenario simulation example where the *maximum computational time* was about 78% of T_c and the mission total time equals to 7.16 s.

Three obstacles scenario

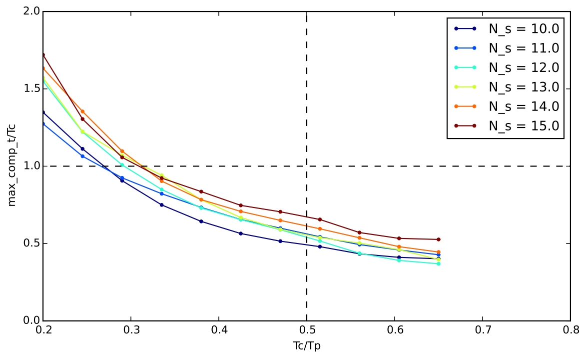
For this new scenario, a greater impact of the number of samples (N_s) and number of non-null internal knots (N_{knots}) is observed. The greater the N_{knots} or the N_s the greater is the *maximum computational time*/T_c. This behavior is the one expected since the number of constraints and the number of arguments for the cost function to be minimized depend on these two parameters respectively.



(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}



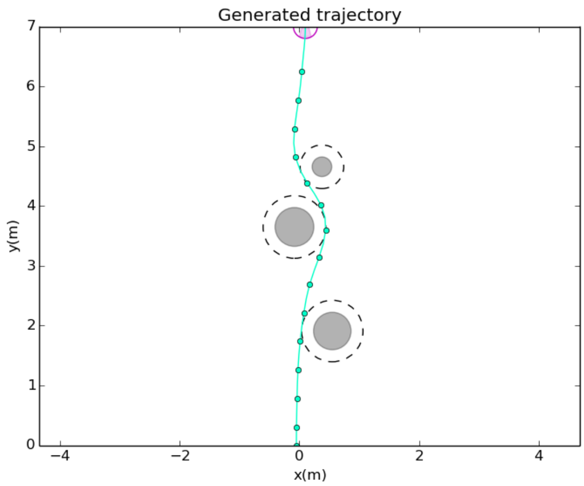
(c) Six internal knots. Average variance between lines is 0.587×10^{-2}

Figure 3.4 – Three obstacles scenario.

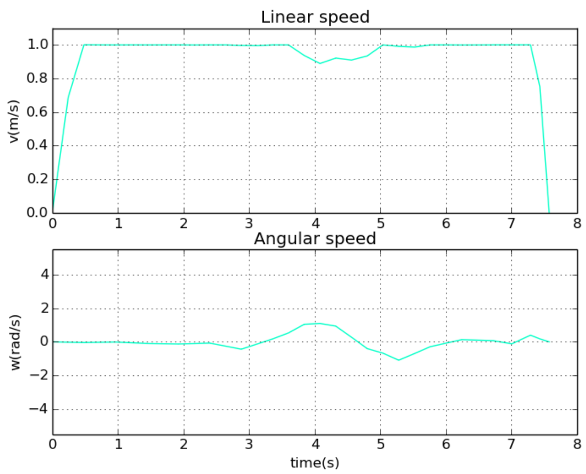
Again, in the figure 3.3 we show a simulation example run with the parameters' values presented in table 3.4.

Table 3.3 – Motion planner 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) Robot's path.

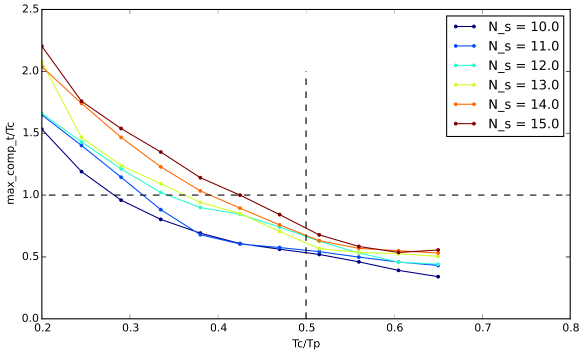


(b) Robot's input.

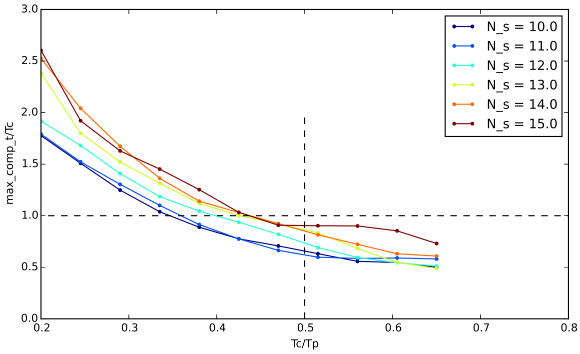
Figure 3.5 – Three obstacle scenario simulation example where the *maximum computational time* was about 84% of T_c and the mission total time equals to 7.57 s.

Six obstacles scenario

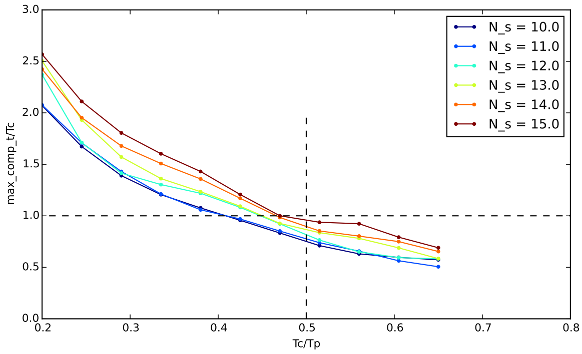
As for the scenario with six obstacles we realize that the observations for the latest scenario are accentuated.



(a) Four internal knots. Average variance between lines is 2.272×10^{-2}



(b) Five internal knots. Average variance between lines is 2.635×10^{-2}



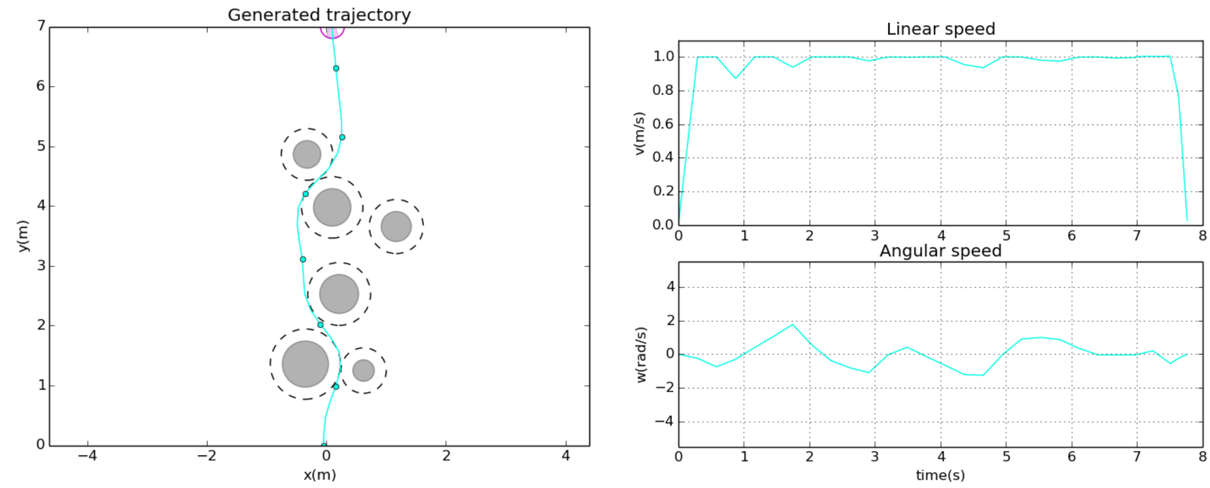
(c) Six internal knots. Average variance between lines is 1.526×10^{-2}

Figure 3.6 – Six obstacles scenario.

add compt time X max number of detected obsts

Table 3.4 – Motion planner main parameters

T_p	3.20 s
T_c	1.28 s
N_s	12
N_{knots}	6
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	$[-0.35\ 1.36\ 0.39]$
O_1	$[0.21\ 2.53\ 0.33]$
O_2	$[-0.32\ 4.86\ 0.23]$
O_3	$[0.10\ 3.98\ 0.31]$
O_4	$[0.62\ 1.25\ 0.18]$
O_5	$[1.17\ 3.66\ 0.25]$



(a) Robot's path.

(b) Robot's input.

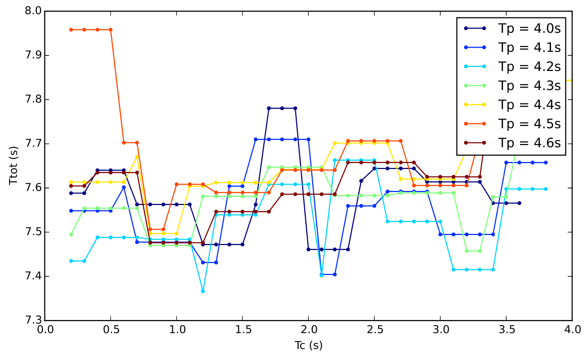
Figure 3.7 – Three obstacle scenario simulation example where the *maximum computational time* was about 90% of T_c and the mission total time equals to 7.76 s.

3.4.2 Total time analysis

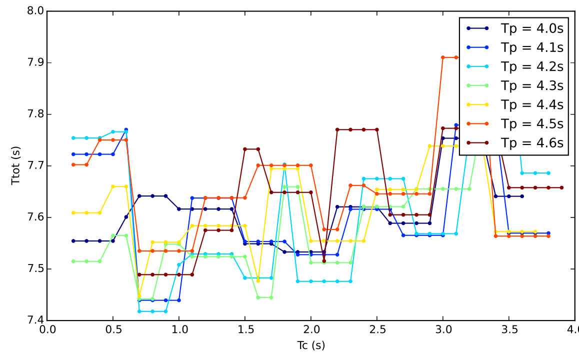
The time spend for finding the solution for a given set of parameters values does not impact the solution it self. Let's analyze then how the solution behaves for different scenarios.

Two important notions when trying to quantify a solution fitness are the total time spend for completing the mission and the robot-to-obstacle distance.

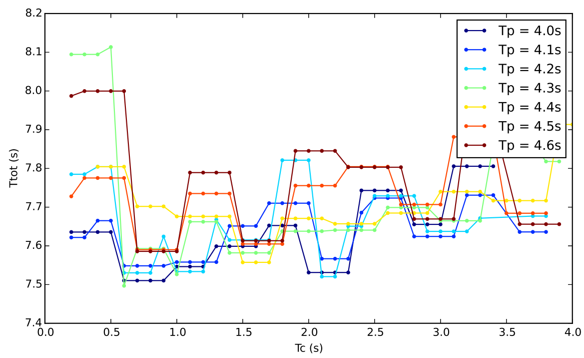
Figure 3.8 show how the time spend for completing the mission behaves with respect to three parameters: T_c, T_p, N_s.



(a) $N_s = 10$



(b) $N_s = 11$



(c) $N_s = 12$

Figure 3.8 – Variation of total mission time with the computation horizon (T_c) for differet planning horizons (T_p) and N_s and three obstacles.

We observe an overall tendency that for a given number of internal knots and N_s the total mission decreases as the planning horizon decreases. This can be explained by the fact that the trajectory quality is increased and is closer to an optimal solution for a greater density of knots within a planning horizon.

One may notice as well that the total mission time is invariant with respect to T_c in the sense that no pattern can be observed besides oscillations of the total time due to the scenario specific configuration.

Get no obstacles information too

Robot to obstacle distance

The second parameter to measure the solution fitness is the robot-to-obstacles distance. In order to simplify this measure we introduce the notion mean penetration of the robot during its mission. We take

— Distance inter robots

— Min dist to obstacles

3.4.3 Obstacle penetration

The total obstacle penetration area (P) can be calculated as the some of the penetration area for a planning section (P_w), that is the plan followed within a computation horizon. P_w for a round obstacle can be estimated as follows:

$$\mathrm{P}_w \simeq \frac{T_c}{N_{Tc}} \sum_{o=0}^{M-1} \sum_{k=0}^{N_{Tc}} \frac{r_o p_k - \frac{p_k^2}{2}}{r_o - p_k} v_k$$

where r_o is the radius of the oth obstacle, p_k is the length of the penetration and v_k is the linear velocity for a given time instant k within the computing horizon w.

As expected, the greater the N_{ssol} (which in turn increases N_{Tc}) the more accurate is the area found. We show in Figure 3.9 that the area value converges to the precise area as N_{ssol} increases.

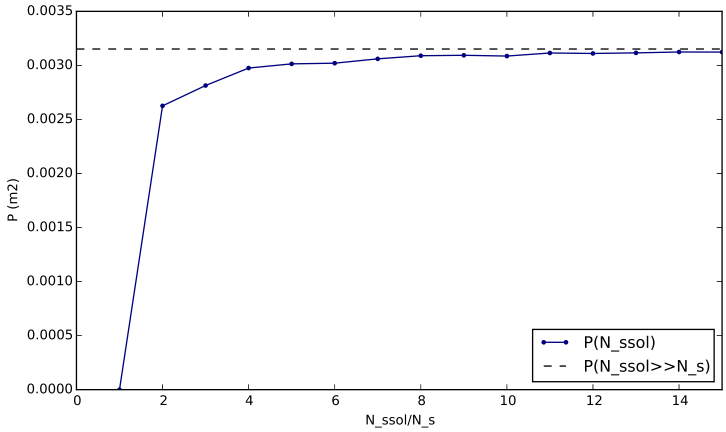


Figure 3.9 – Convergence of the area computation.

After some tests we saw that a good estimate for the penetration area can be found using $N_{ssol} > 10N_s$.

Ideally we would have $\mathrm{P}_w = 0$. A way of guarantying that would be to increase the obstacles radius computed by the robot's perception system by the maximum distance that the robot can run within the time spam T_p/N_s (equivalent to T_c/N_{T_c}). This approach presents a

Influence of N_s on penetration area

As state before in subsection or section TODO the sampling was the most sensible parameter regarding the computation time. The greater the number of samples the greater the number of inquations constraints and consequently the computation time for solving the NLP. Now, analyzing the impact of the sampling on the penetration area we see that the greater the number of samples the smaller is the penetration area (as expected). In Figure 3.10 we see that we have a linear relation between this two variables.

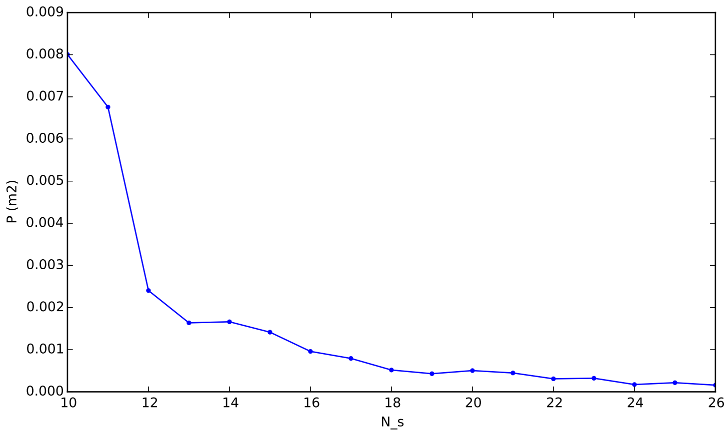


Figure 3.10 – Penetration area varying with N_s.

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Appendix A

Random Graphs

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