

Parking Algorithm based on Multiple Paths (pending to update)



Alejandro D.J Gomez Florez, November 26, 2025
Chair of Ms Applied Mathematics | Universidad EAFIT

Contents

1 · Introduction	1
1.1 · Problem Definition	1
2 · Related Work	1

1 · Introduction

1.1 · Problem Definition

In this work, we develop a probabilistic algorithm to address the autonomous parking problem. We model the vehicle as a point mass in a 2D plane with position and orientation, following the unicycle kinematic model. The vehicle's state is represented by the vector $X = (x, y, \theta)^T$, where (x, y) denotes the position and θ represents the orientation angle. The continuous-time dynamics are governed by:

$$\dot{X} = \begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} v \cos(\theta) \\ v \sin(\theta) \\ \omega \end{pmatrix}$$

where v is the linear velocity and ω is the angular velocity, which constitute the control inputs $u = (v, \omega)^T$ to the vehicle. For implementation purposes, we discretize this model and formulate it as a discrete-time state-space system:

$$X_{k+1} = f(X_k, u_k) + w_k$$

where X_k represents the state at time step k , $f(\cdot, \cdot)$ is the nonlinear state transition function obtained by discretizing the unicycle dynamics, and $w_k \sim \mathcal{N}(0, Q)$ represents the process noise accounting for model uncertainties and disturbances.

In the autonomous parking problem, a mobile vehicle must move from a set of initial positions towards a target pose known as the **docking pose**. However, the actual location of the vehicle is not perfectly known; it is affected by various sources of uncertainty such as sensor noise, odometry errors, and changes in environmental conditions.

To represent this uncertainty, the vehicle's state is no longer modeled as a deterministic pose $X = (x, y, \theta)^T$, but rather as a probability distribution over that state. A common approach is to use a Gaussian model, where the vehicle maintains a *belief* defined as $b = \mathcal{N}(\mu, P)$, where μ is the mean pose and P is the associated covariance matrix.

1.1.1 · Really Small Stuff

2 · Related Work