# Robot Mobility: Lecture 7 Lecture Notes

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November 2, 2023

## 0.1 Recap

Predict both

- States
- Control input

We optimize a sequence of control inputs, but we only implement the first input, and the reoptimize. Sometimes due to missed timing, we can implement not the first, but the second or third contol input.

## 1 Model Predictive Control II

#### Constraints

- Slew
- State constraint Z
- And one more

E, F, and G linear in-equality constraints

We want to express the constraints in terms of  $\Delta U$ , which should be  $\leq$  some terms which does not depend on  $\Delta U$ .

## 1.1 Infeasibility

Unconstrained Infeasible for the system to execute the desired control input. Constrained Because of disturbance or uncertainty, the control input may be thrown outside of the constraints. Therefore the control input can become infeasible, and then for future optimizations, from an infeasible state, then the system can very easily become very infeasible.

There are different ways to account for this: Ad hoc strategies

- Apply the previous control input.
- Apply the controller  $\hat{u}(k+1|k)$  or  $\hat{u}(k+2|k)$  computed last time.

Systematic strategies:

- Avoid hard constraints (softening the constraints)
- Actively manage the constraints and/or the horizons at each time

### 1.1.1 Soft constraints

We introduce the slack variables  $\epsilon$  The  $\epsilon$  is both in the constraints and also in the constraints. That means if  $\epsilon \geq 0$ , then the cost function is also penalized. This way it is only used if it is absolutely possible.

## 1.1.2 Stability

Maybe Stability is only defined within the horizon. We can guaranty stability in two ways:

- terminal constraints We set the last predicted state e.g. equal to 0. Note that the 0 is the equibrium point and not a scalar.
- $\bullet$  inifinite horizon