

ME 290J
Model Predictive Control
for Linear and Hybrid Systems

Francesco Borrelli

Spring 2011
Department of Mechanical Engineering
University of California
Berkeley, USA



Instruction

- **Instructor:** Francesco Borrelli, Room 5139 EH, 643-3871,
fborrelli@berkeley.edu
Office Hours: Tu and Th 3.30-4.30
- **Teaching Assistant:** None – might change.
- **Lectures:** Tu-Th 2-3.30 Room 81, Evans Hall
- **Class Notes:** Slides distributed before (sometime after) the class
- **Class Web Site:** bSpace

Matlab

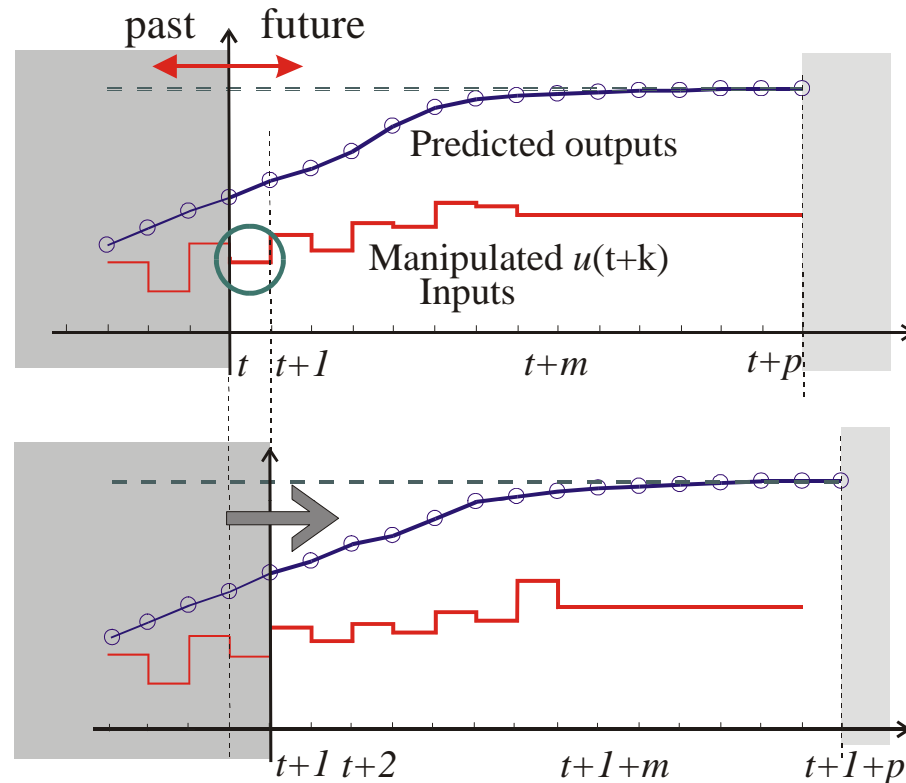
- Matlab running the computers in 2109 Etcheverry Hall
- Card key access required
- I will submit class list to so that everyone in the class has access to that room
 - Please enroll in the class ASAP
- **Need** additional toolbox/Software distributed through bSpace

Grading

- **20% Homework**
- **50% Final Project**
- **30% Oral or Final Test**

ME290J Overview

Model Predictive Control



- Optimize at time t (new measurements)
- Only apply the first optimal move $u(t)$
- Repeat the whole optimization at time $t+1$
- Optimization using current measurements ☐ Feedback

MPC Algorithm

$$\begin{aligned} & \min_U \sum_{k=t}^{t+N-1} l(x_k, u_k) \\ \text{subj. to } & \begin{cases} x_{k+1} = f(x_k, u_k), \quad k = t, \dots, t+N-1 \\ u_k \in \mathcal{U}, \quad k = t, \dots, t+N-1 \\ x_k \in \mathcal{X}, \quad k = t, \dots, t+N-1 \\ x_t = x(t) \end{cases} \end{aligned}$$

At time t:

- Measure (or estimate) the current state $\mathbf{x}(t)$
- Find the optimal input sequence $U^* = \{u_t^*, u_{t+1}^*, u_{t+2}^*, \dots, u_{t+N-1}^*\}$
- Apply only $u(t) = u_t^*$, and discard $u_{t+1}^*, u_{t+2}^*, \dots$

Repeat the same procedure at time $t+1$

Multivariable, Model Based

Nonlinear, Constraints Satisfaction, Prediction

Important Issues in Model Predictive Control

Even assuming perfect model, no disturbances:

predicted open-loop trajectories
 \neq
closed-loop trajectories

- **Feasibility**

Optimization problem may become infeasible at some future time step.

- **Stability**

Closed-loop stability is not guaranteed.

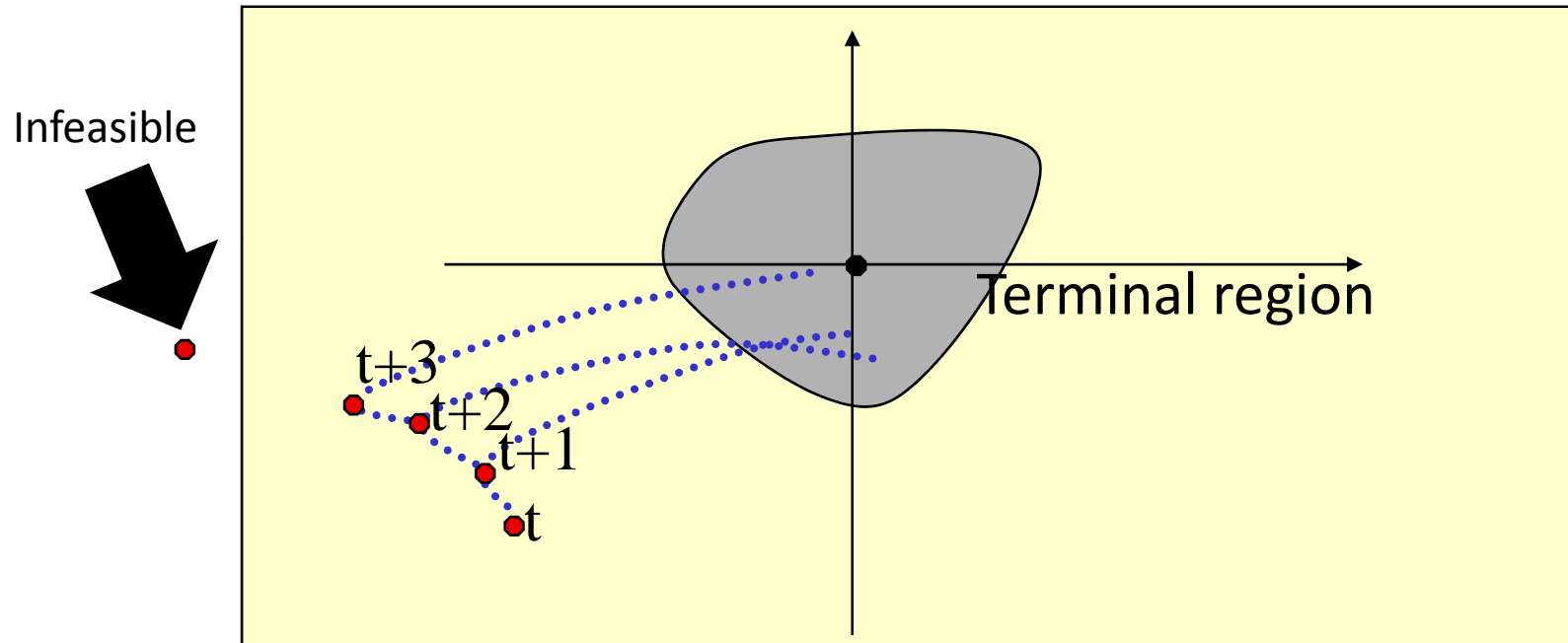
- **Performance**

Goal: $\min \sum_{k=t}^{\infty} l(x_k, u_k)$

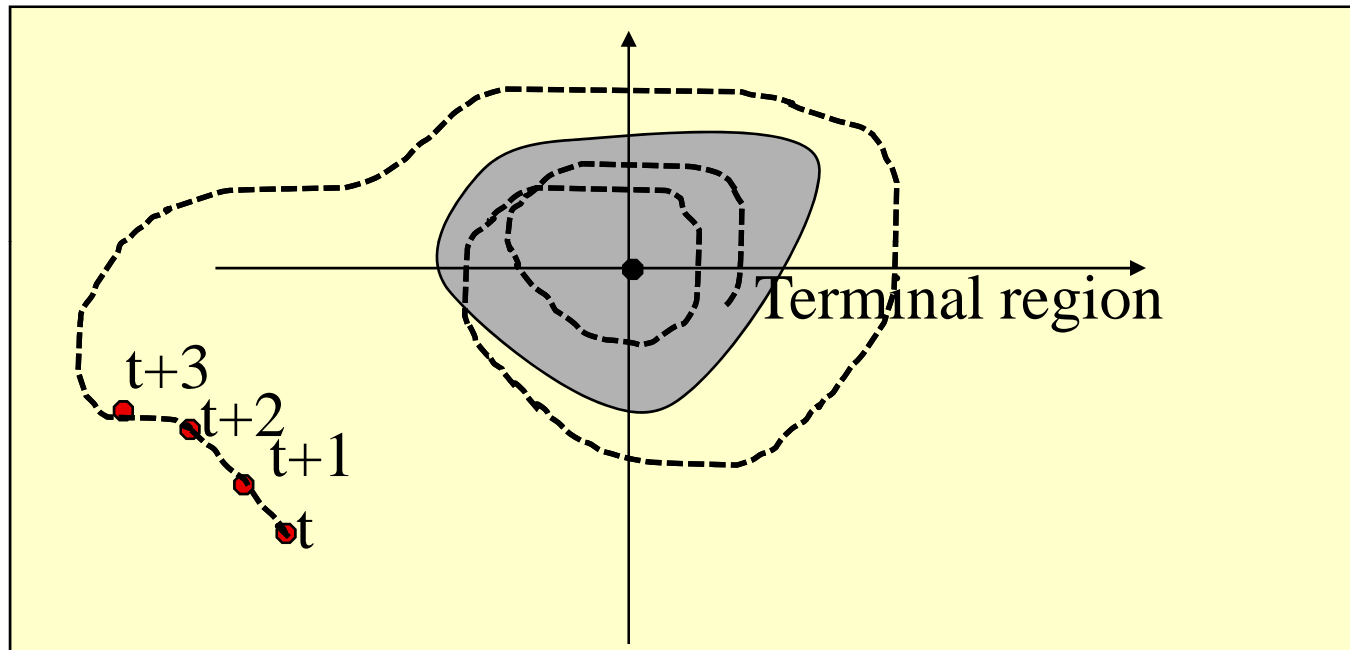
What is achieved by repeatedly minimizing $\min \sum_{k=t}^{t+N} l(x_k, u_k)$

- **Real-Time Implementation**

Feasibility Issues



Stability Issues



Feasibility and Stability Constraints

$$\begin{aligned} \min_U \quad & \sum_{k=t}^{t+N-1} l(x_k, u_k) + p(x_{t+N}) \\ \text{subj. to} \quad & \begin{cases} x_{k+1} = f(x_k, u_k), \quad k = t, \dots, t+N-1 \\ u_k \in \mathcal{U}, \quad k = t, \dots, t+N-1 \\ x_k \in \mathcal{X}, \quad k = t, \dots, t+N-1 \\ x_{t+N} \in \mathcal{X}_f \\ x_t = x(t) \end{cases} \end{aligned}$$

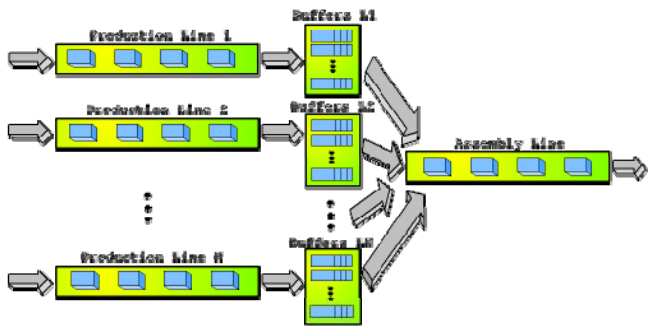
Modified Problem

(Large Body of Literature)

\mathcal{X}_f (Robust) Invariant Set

$p(x)$ Control Lyapunov Function

Real Time Implementation



Summarizing...

Need:

- A discrete-time model of the system
(Matlab, Simulink)
- A state observer
- Set up an Optimization Problem
(Matlab, MPT toolbox/Yalmip)
- Solve an optimization problem
(Matlab/Optimization Toolbox, NPSOL, NAG, Cplex)
- Verify that the closed-loop system performs as desired (avoid infeasibility/stability)
- Make sure it runs in real-time and code/download for the embedded platform

Class Topics

(Subject to changes)

Week 1: Introduction and Fundamentals of Optimization

Week 2/3: Fundamentals of Optimization.

Week 4: Multiparametric Programming.

Week 5. Convex and Mixed-Integer Multiparametric Programming

Week 6: Review of Optimal Control Theory and Dynamic Programming

Week 7: Invariant Set Theory

Week 8/9: Constrained Optimal Control for Linear Systems

Week 10: Predictive Control: Fundamentals

Week 11: Predictive Control: Stability and Feasibility Theory

Week 12/13: Hybrid systems

Week 14: Predictive Control for Hybrid Systems.

Week 15/16: Applications/Case Studies

Class Goals

- Predictive Control Theory
- Design and Implement an MPC Controller in Matlab
- Computational Oriented Models of Hybrid Systems

Initial Remarks

- **MPC Name**
- Continuous-Time versus Discrete-Time
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- Non trivial examples
- What I'd like to add:
 - Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Initial Remarks

- MPC Name
- **Continuous-Time versus Discrete-Time**
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- Non trivial examples
- What I'd like to add:
Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Why Not Continuous Time Optimization?

$$\begin{aligned} J^*(x(t)) = & \min_{u_{[t:t+N]}} \int_t^{t+N} l(x(\tau), u(\tau)) d\tau \\ \text{subj.to} & \quad \dot{x}(\tau) = f(x(\tau), u(\tau)), \quad \tau \in [t, t+N] \\ & \quad x(\tau) \in \mathcal{X}, \quad \tau \in [t, t+N] \\ & \quad u(\tau) \in \mathcal{U}, \quad \tau \in [t, t+N] \end{aligned}$$

- Choice of this course
- Issues are the same
- Soon or later need to discretize
- Software exists (Example: <http://tomdyn.com/>)

Initial Remarks

- MPC Name
- Continuous-Time versus Discrete-Time
- **MPC in Practice**
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- Non trivial examples
- What I'd like to add: Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

MPC in Practice

- Second Most Used Control Methodology after PID

Qin, S. J. and T. A. Bagdwell (2003). A survey of model predictive control technology. Control Engineering Practice 11, 733-764

- Persistent Control Community Interest (see ACC, CDC proceeding)

Initial Remarks

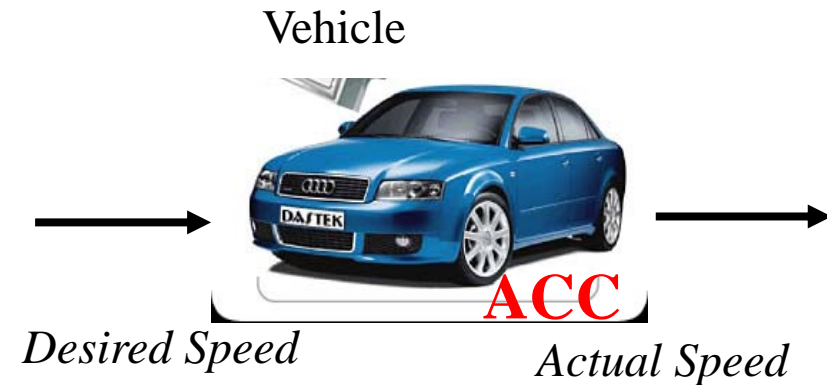
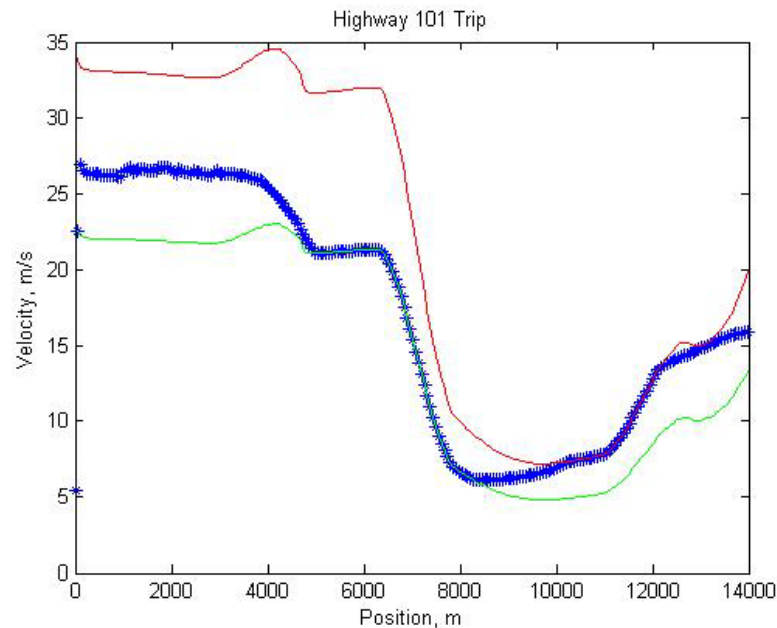
- MPC Name
- Continuous-Time versus Discrete-Time
- MPC in Practice
- **Difficulty : The theoretical side and the computation side**
- Two simple examples Models and Simulations
- Non trivial examples
- What I'd like to add: Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Initial Remarks

- MPC Name
- Continuous-Time versus Discrete-Time
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- **Two simple examples - Models and Simulations**
- Non trivial examples
- What I'd like to add: Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Example 1

Audi SmartEngine

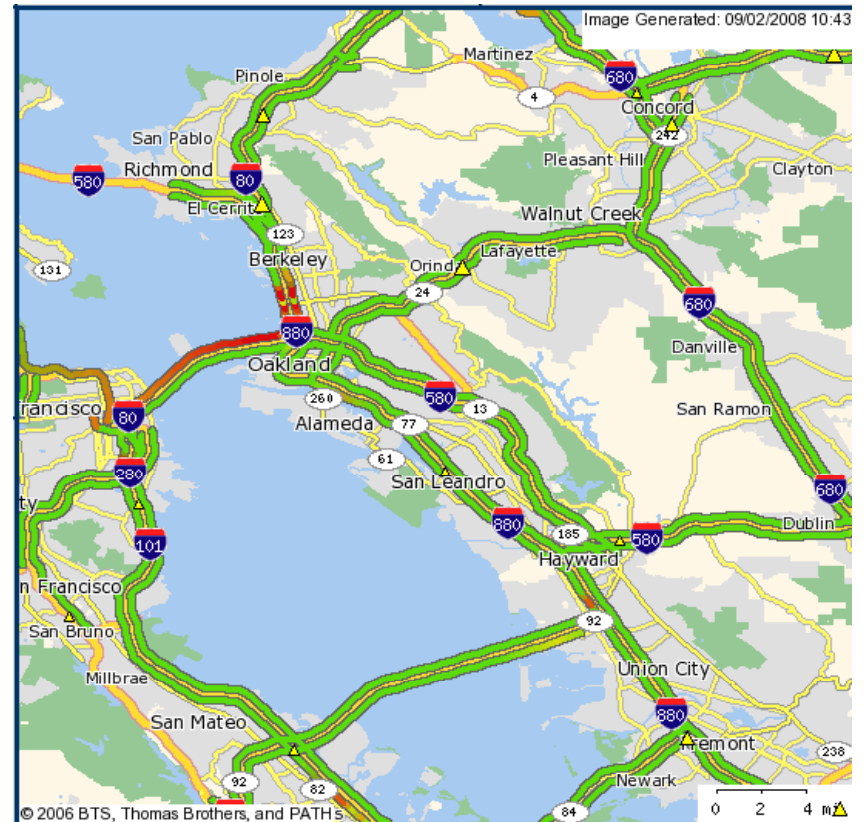


- Design and MPC Controller regulating the desired speed (through an Automatic Cruise Control) in order to reach the destination in the most fuel-efficient way
- Prediction: Max and Min Speed of traffic, Grade
- Constraints: Max and Min Speed (of traffic and of vehicle)

Example 1

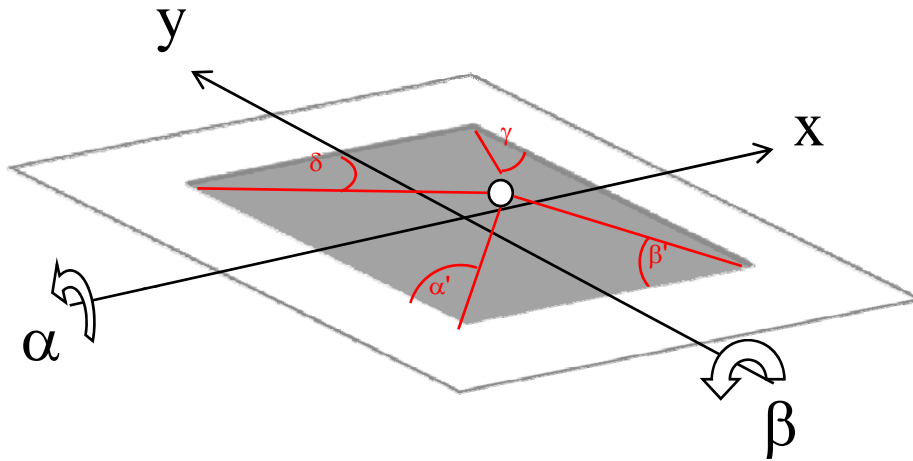
Data from PeMS

- California Freeway Performance Measurement System
- Collects real-time data on CA freeways via loop detectors
- Able to communicate average traffic speed at loop location every 5 minutes
- Loops typically positioned every 0.3-3 miles



Example 2

Ball and Plate Experiment



- **Specification of Experiment:**

Angle: $-17^\circ \dots +17^\circ$, Plate: $-30 \text{ cm} \dots +30 \text{ cm}$

Input Voltage: $-10 \text{ V} \dots +10 \text{ V}$

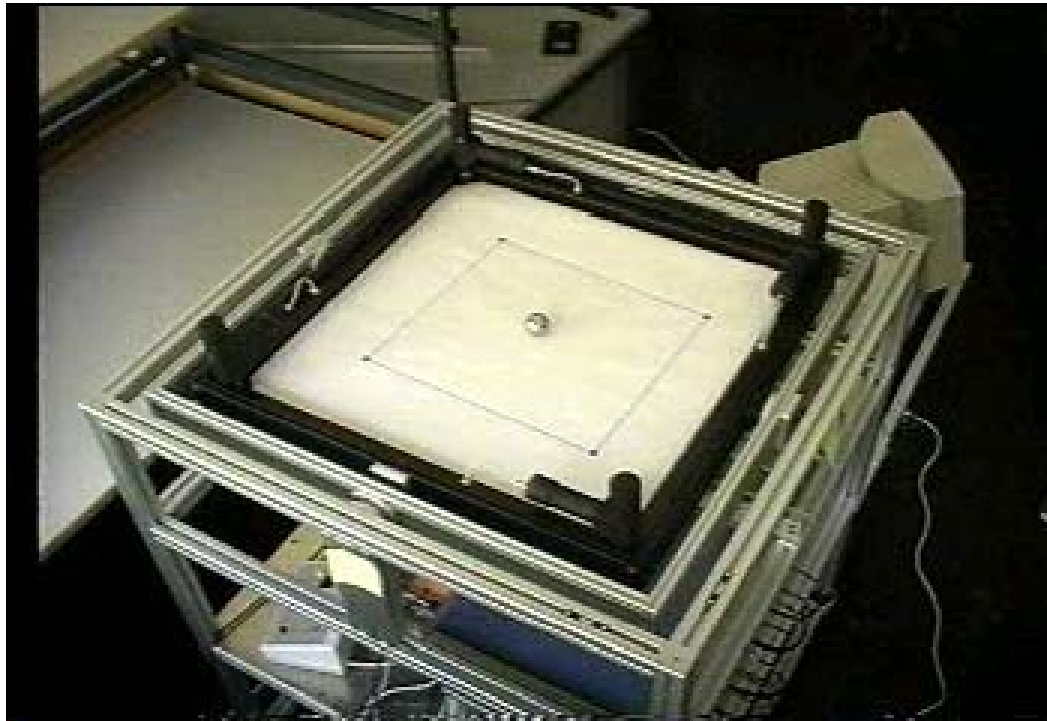
Computer: PENTIUM166

Sampling Time: 30 ms



Example 2

Ball and Plate Experiment



Initial Remarks

- MPC Name
- Continuous-Time versus Discrete-Time
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- **Non trivial examples**
- What I'd like to add: Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Catalytic Cracker

Open Folder

Predictive Control in NeuroScience

- **16:05 Open Folder**

Initial Remarks

- MPC Name
- Continuous-Time versus Discrete-Time
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- Non trivial examples
- **What I'd like to add:**
Distributed, Robust, Probabilistic, Soft-Constraints
- Any preference for examples?

Initial Remarks

- MPC Name
- Continuous-Time versus Discrete-Time
- MPC in Practice
- Difficulty : The theoretical side and the computation side
- Two simple examples Models and Simulations
- Non trivial examples
- What I'd like to add:
Distributed, Robust, Probabilistic, Soft-Constraints
- **Any preference for examples?**