Slalom Racing and Flight Dances:

Motion planning, control and learning for high-performance quadrocopter flight

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Lakeside Research Days – July 10, 2013

Institute for Aerospace Studies
UNIVERSITY OF TORONTO

BACKGROUND

Background: Control Engineering

M.Sc. Engineering Cybernetics
M.Sc. Engineering Science & Mechanics

Universität Stuttgart

PhD on robot learning and coordination

with Prof. Raffaello D'Andrea

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

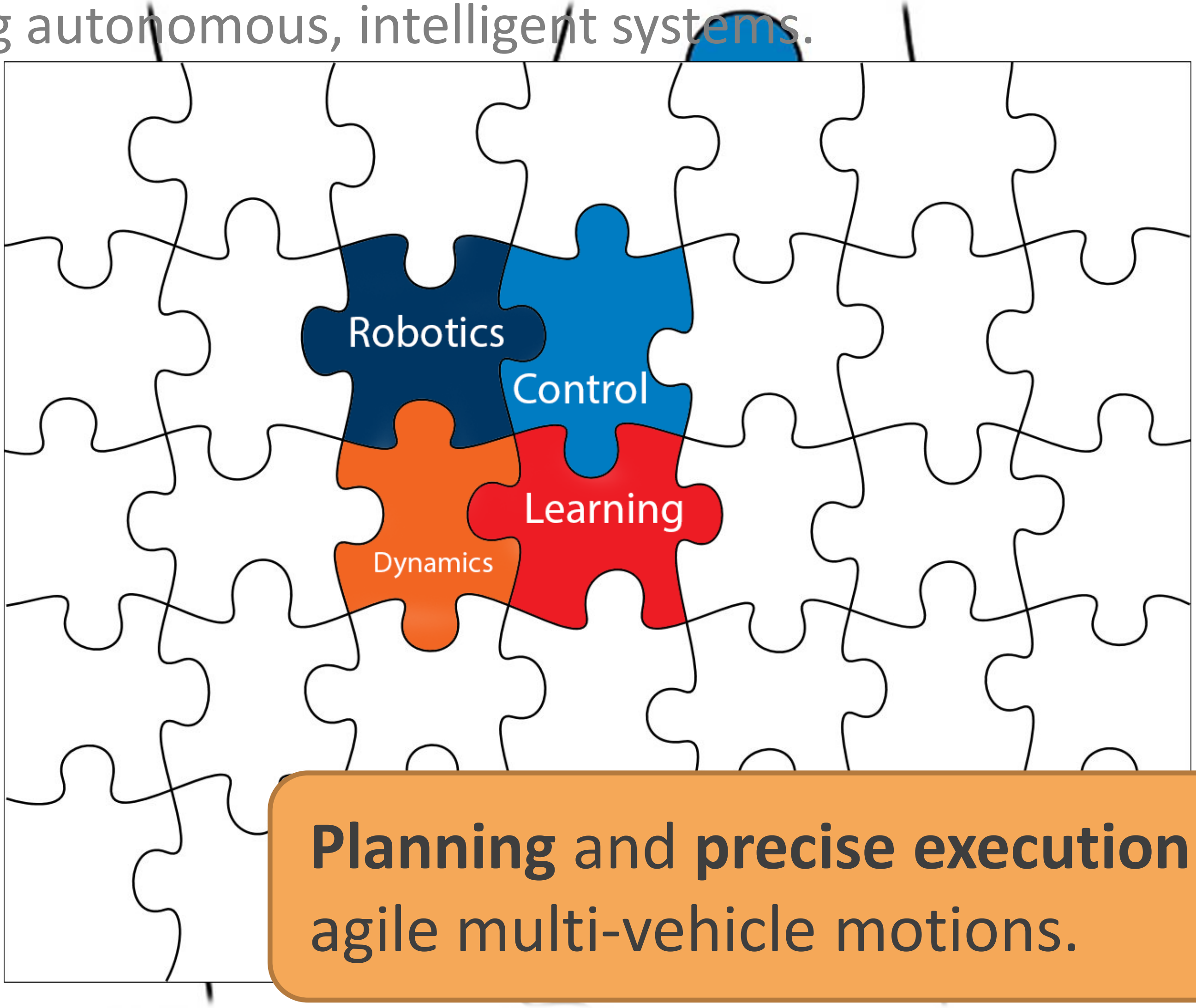
Assistant Professor, Dynamic Systems Lab

since January 2013

UNIVERSITY OF TORONTO

RESEARCH AREA

Developing autonomous, intelligent systems.

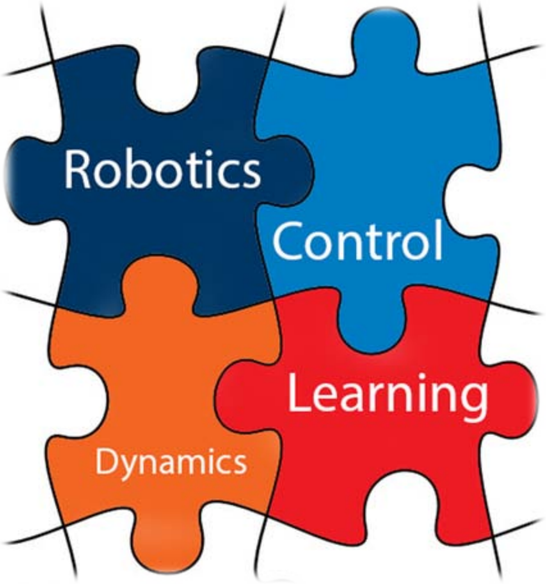


Planning and **precise execution** of agile multi-vehicle motions.

RESEARCH FOCUS

Planning and execution of agile multi-vehicle motions.

Quadrocopter platform.



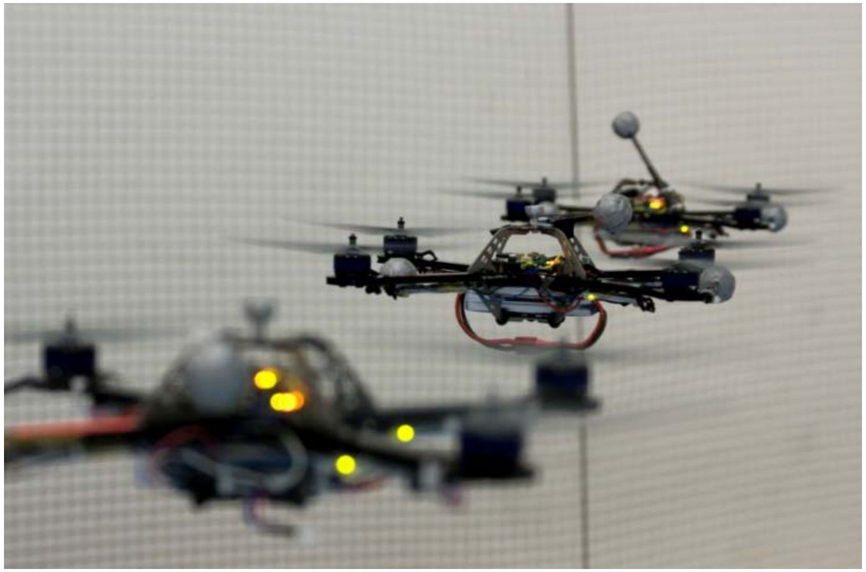
How to guide the vehicle along the desired path?

Which motions are feasible? How to plan collision-free motions?

Can the performance be improved by leveraging past data?

OUTLINE

1. Experimental setup
2. Model-based approach to planning, control and learning
3. Scenario A: Slalom racing
4. Scenario B: Flight dances
5. Summary and Outlook



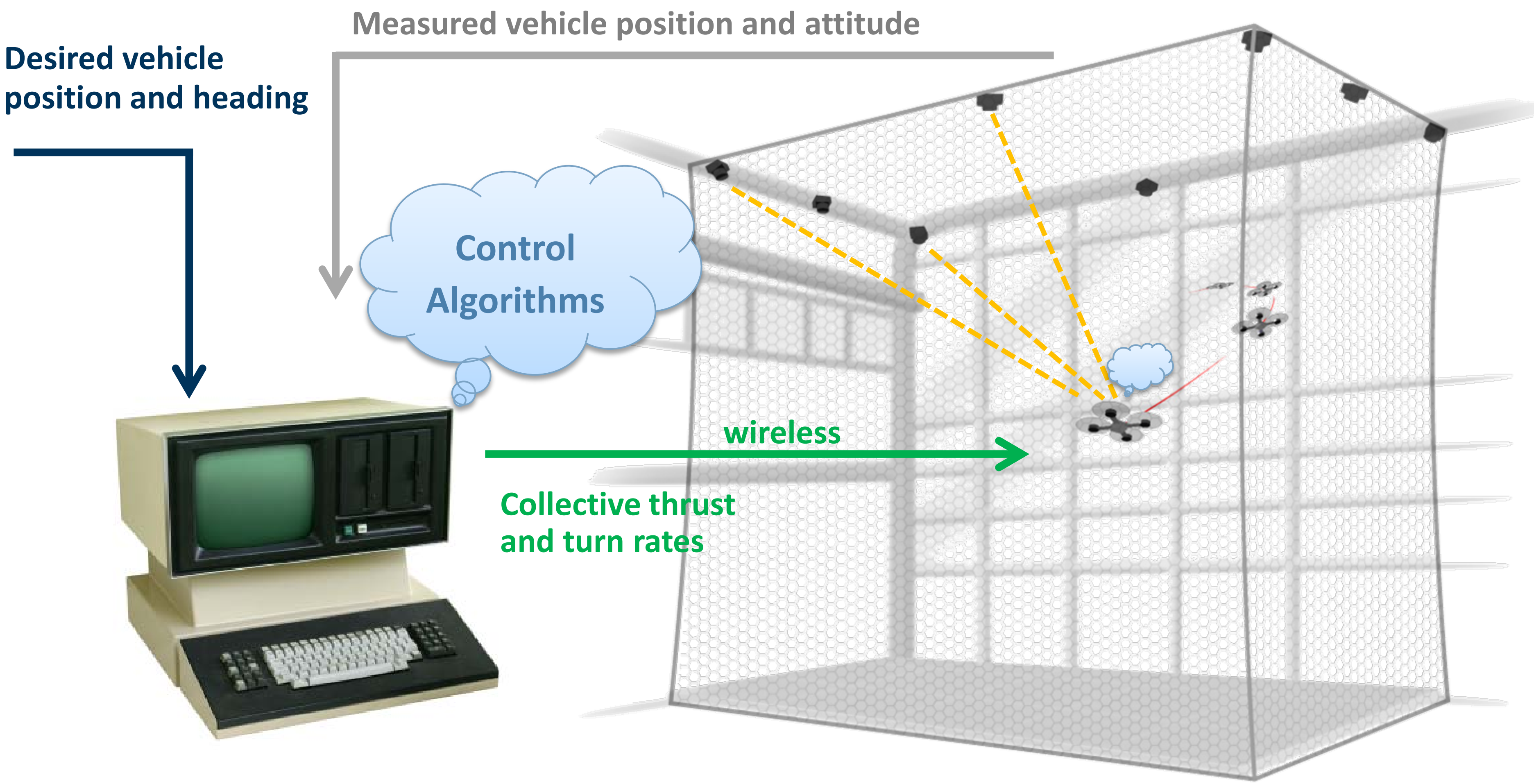
TESTBED


visitor platform →
www.FlyingMachineArena.org
A space where flying robots live and learn.
Institute for Dynamic Systems and Control
IDSC
DMAVT
ETH

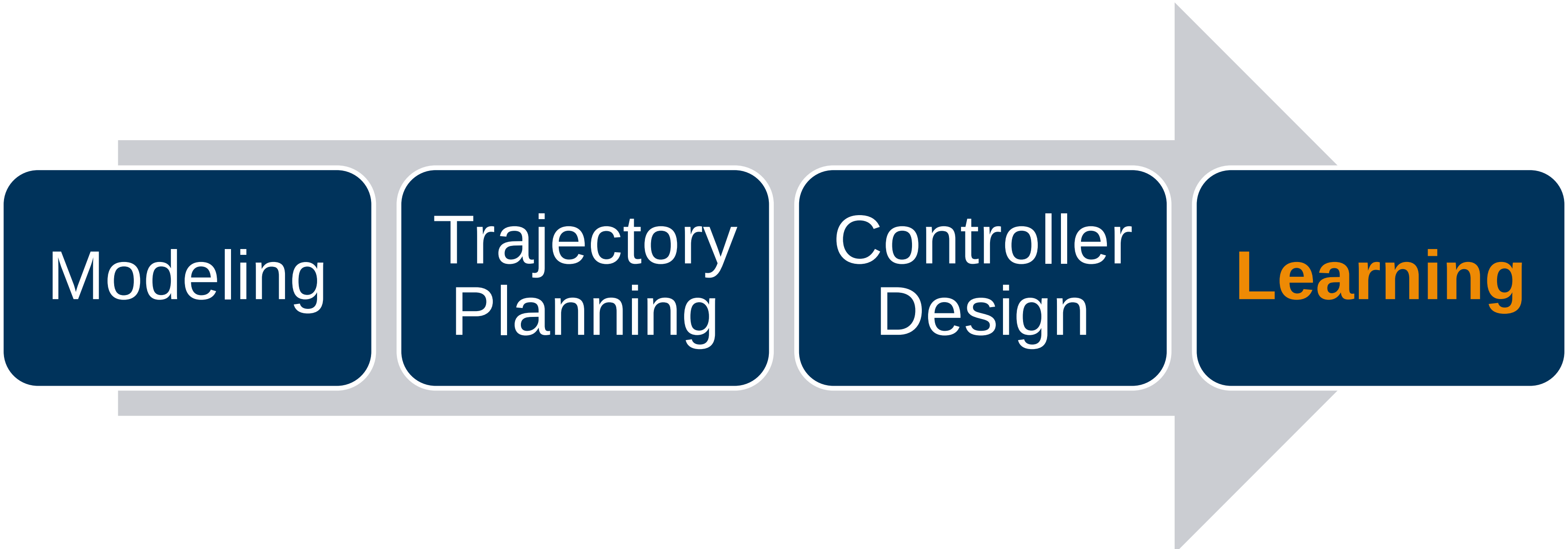
Flying Machine Arena

- http://www.youtube.com/watch?v=pcgvWhu8Arc&feature=c4-overview-vl&list=PLuLKX4lDsLIaVjdGsZxNBKLcogBnVVFQr

EXPERIMENTAL SETUP



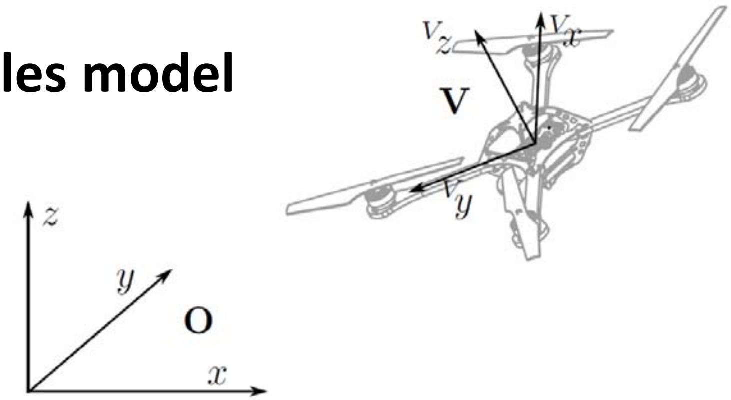
MODEL-BASED APPROACH

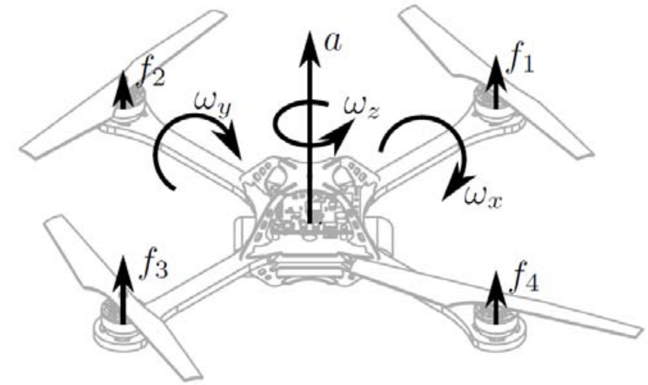


Model-based planning, control and learning.

MODELING

First-principles model





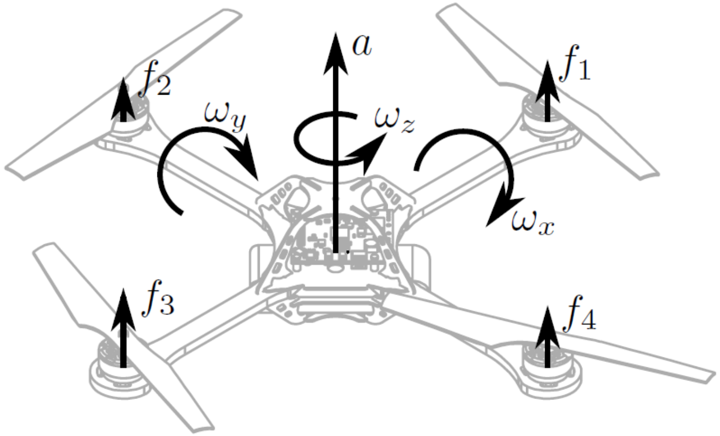
$$^{O}\ddot{x} = {}^{O}_{V}R \begin{bmatrix} 0 \\ 0 \\ a \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}$$

$$I\dot{\omega} = \begin{bmatrix} L(F_2 - F_4) \\ L(F_3 - F_1) \\ k(F_1 - F_2 + F_3 - F_4) \end{bmatrix} - \omega \times I\omega$$

$$f_i = \frac{F_i}{m}, \quad i = 1, \ldots, 4$$

$$\omega = [\omega_x, \omega_y, \omega_z]$$

MODELING



Actuator constraints

$$f_{i,min} \leq f_i \leq f_{i,max} \quad i = 1, \ldots, 4$$

Sensor constraints

$$|\omega_k| \leq \omega_{k,max} \quad k = x, y, z$$

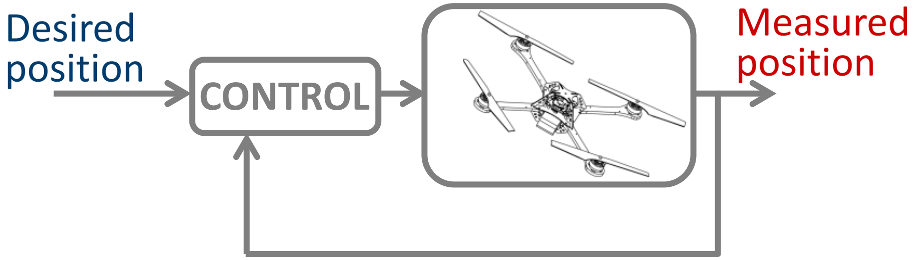
MODEL TELLS US…

Trajectory planning

What is possible? What is easy/difficult?

Control

How to design controller?

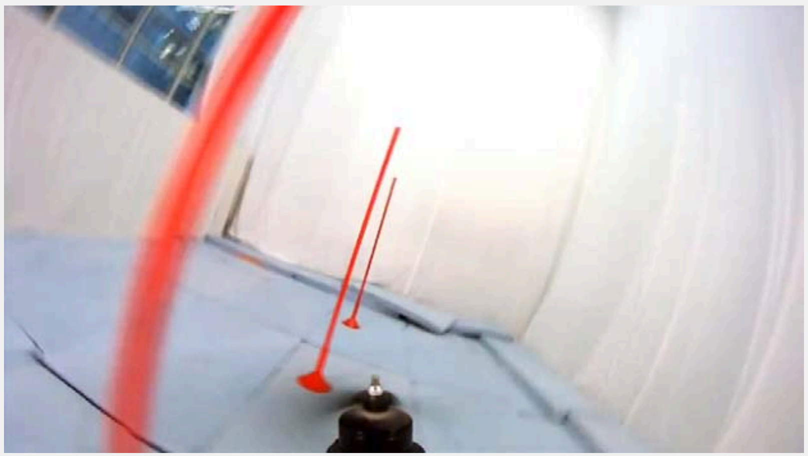


Learning

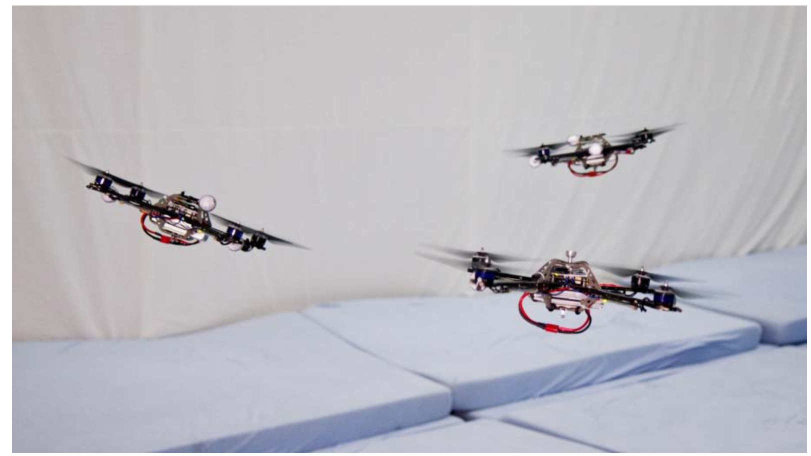
How to compensate for repetitive disturbances?

TWO RESEARCH PROJECTS

A| High-performance slalom racing



B| Coordinated flight synchronized to music



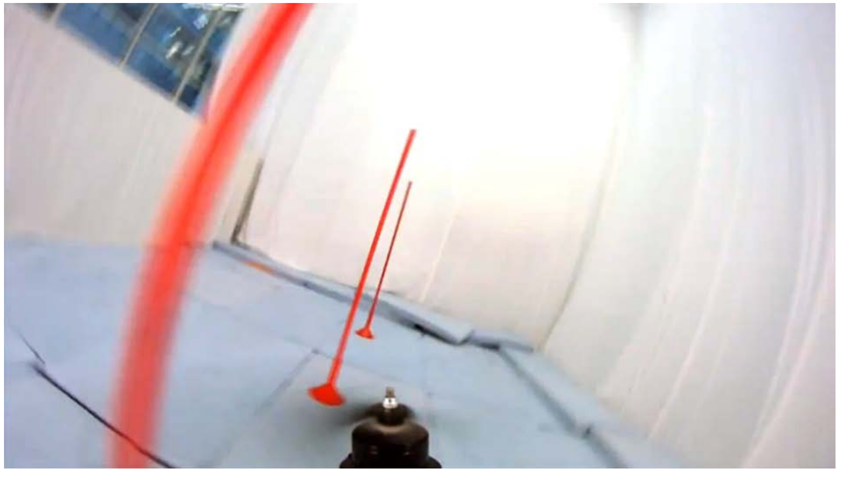
Motivating and demonstrating the developed **trajectory planning,** and **trajectory following and learning** algorithms.

A | TRAJECTORY PLANNING

OBJECTIVE Minimizing the time to complete a given slalom course

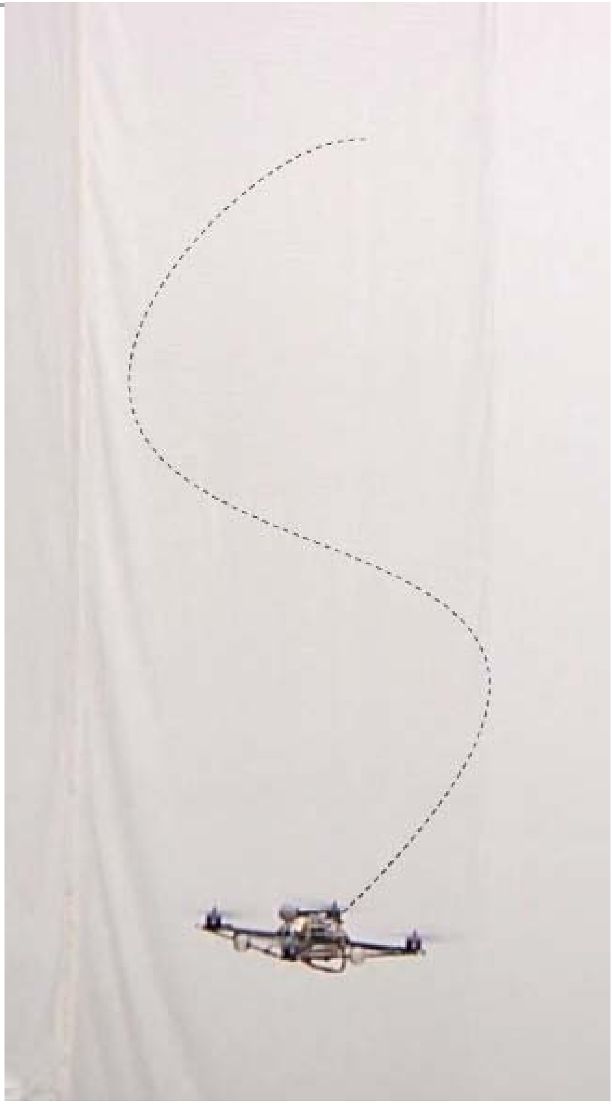
METHOD Nonlinear optimization, offline calculation

1. Plan path around poles
2. Find velocity profile that minimizes the run time and that is feasible with respect to
   - Nominal model
   - Sensor/actuator limits



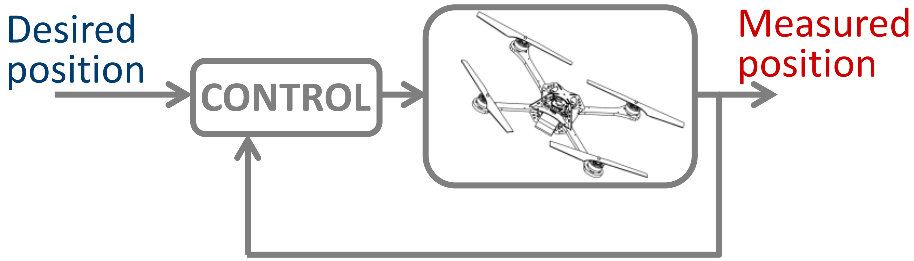
A | TRAJECTORY FOLLOWING

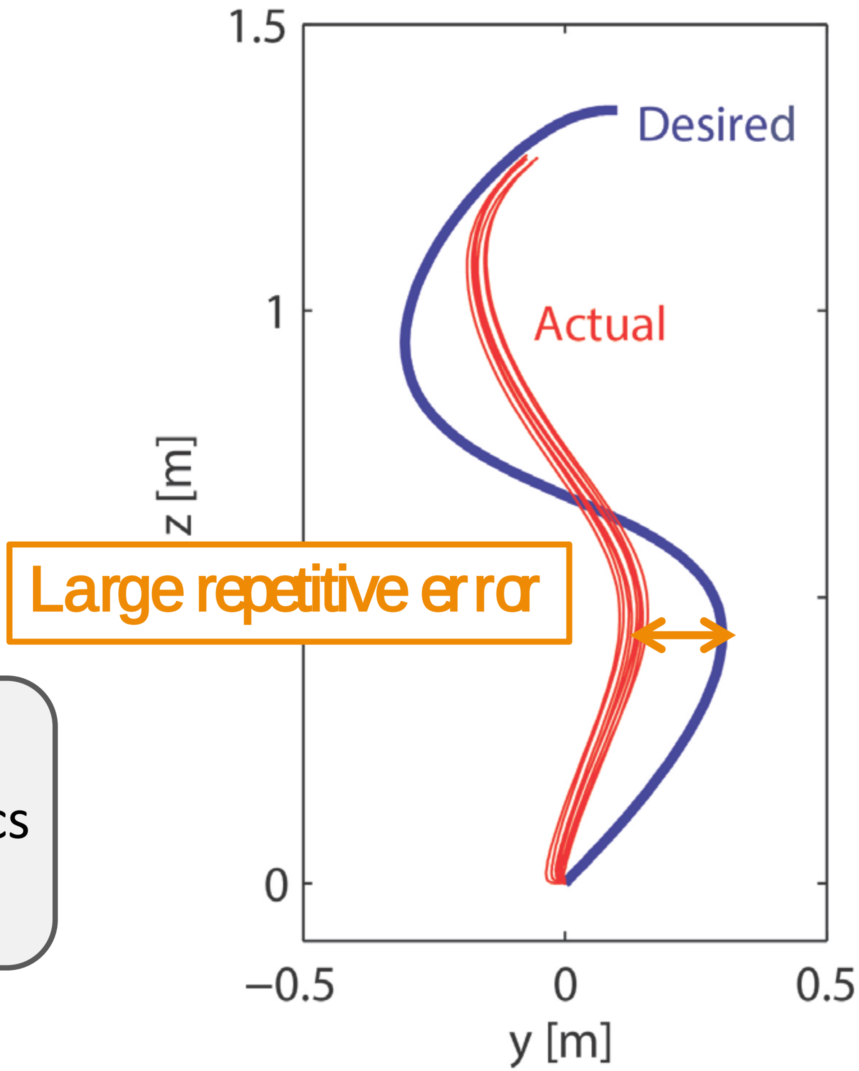
OBJECTIVE Precise tracking of finite-time output trajectory



A | TRAJECTORY FOLLOWING

Typical setup: Feedback control



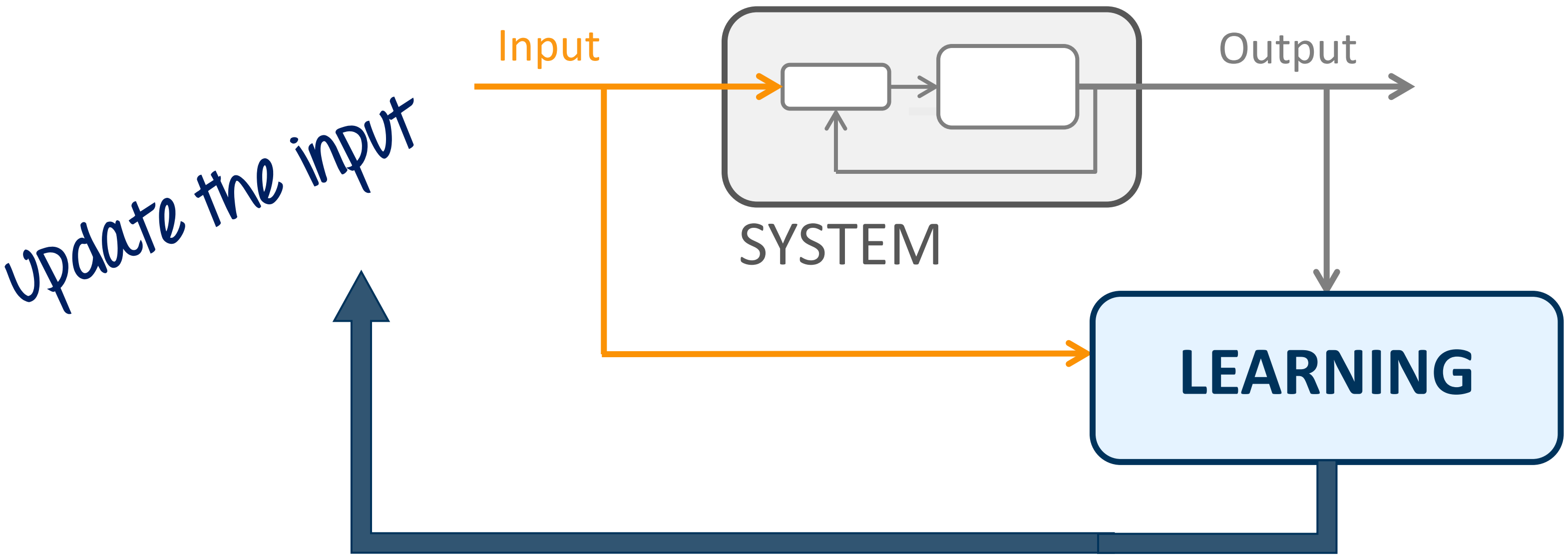


Limitations of feedback control:

– Disturbances & unmodelled dynamics (non-zero mean)

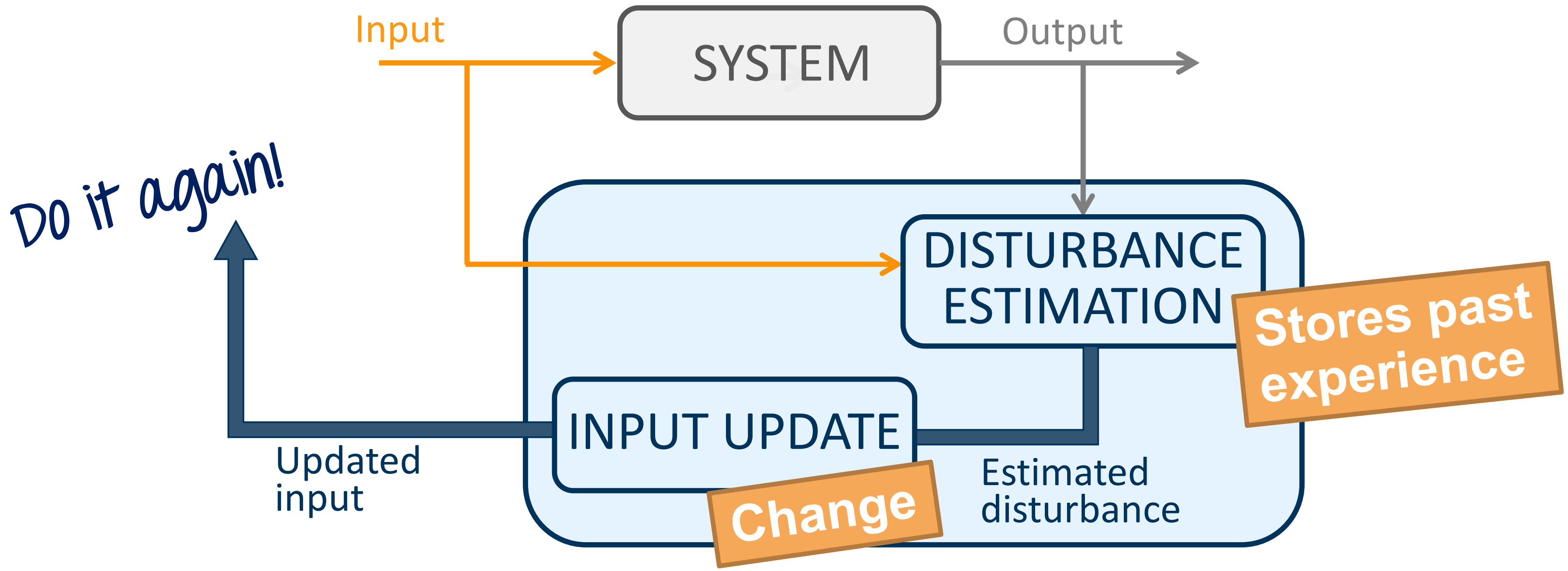
A | TRAJECTORY LEARNING

Improve the performance over causal, feedback control by learning from repeated experiments.



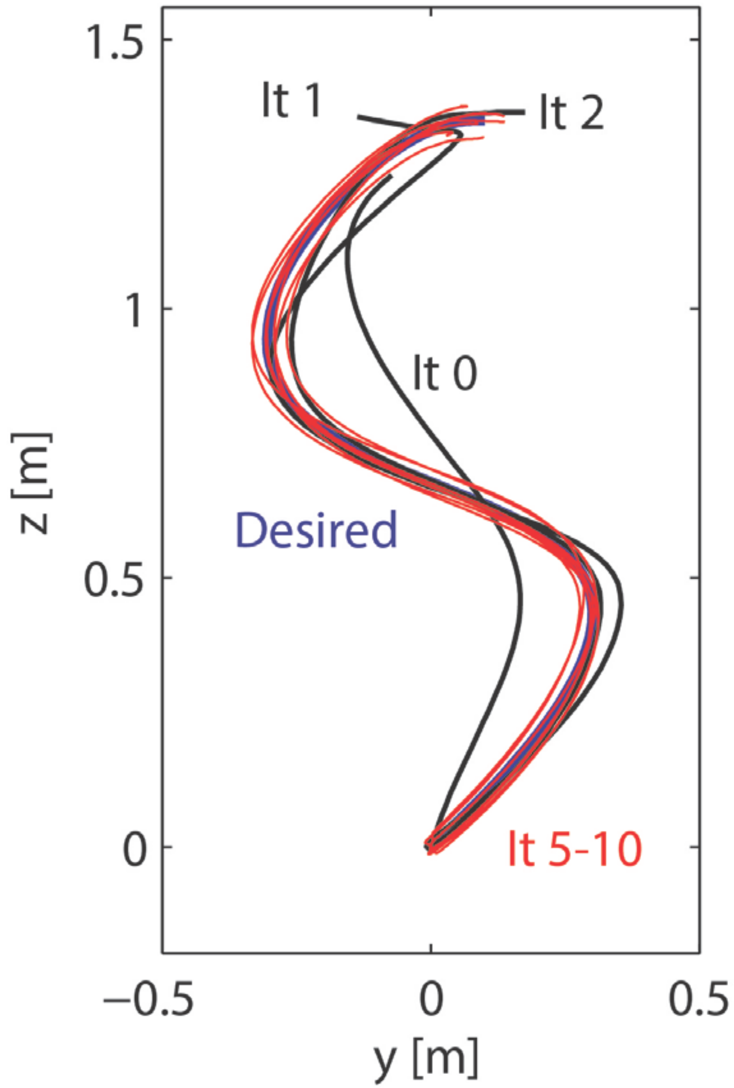
Potential: Acausal action, anticipating repetitive disturbances.

A | TRAJECTORY LEARNING

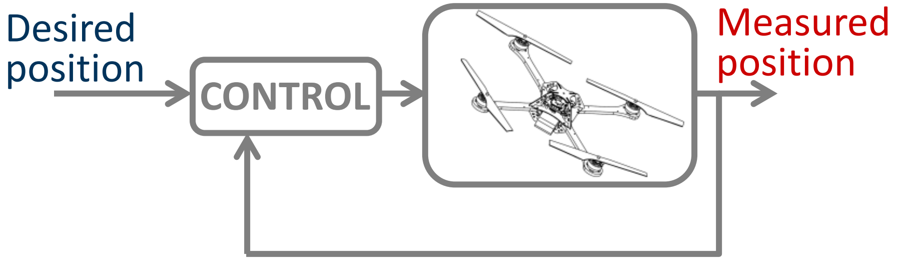


1. Obtain nominal system model analytically or from numerical simulation
2. Estimate model error (after each execution): **Kalman filter**
3. Update **input trajectory: Convex optimization**

A | RESULTS



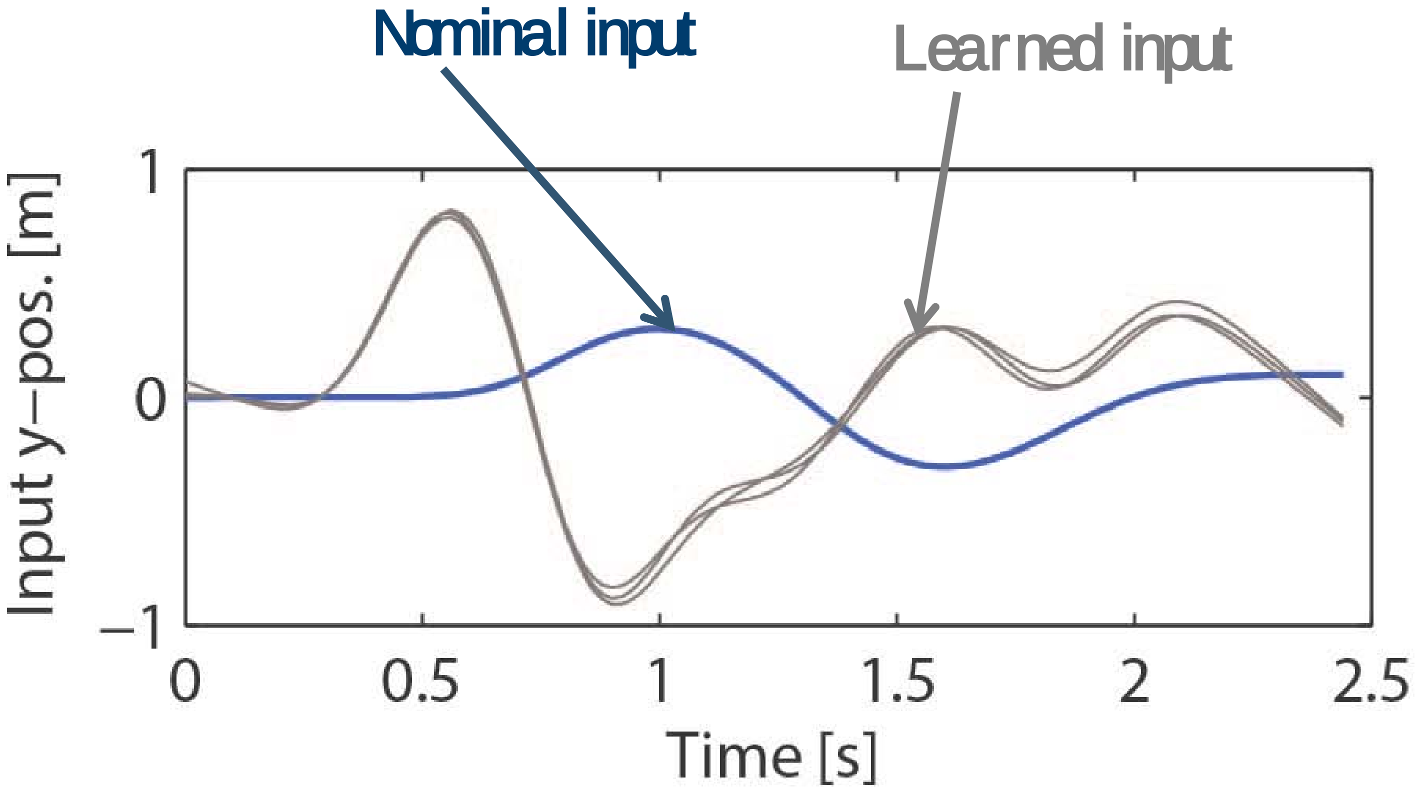
1.5
1
0.5
0
z [m]
It 1
It 2
It 0
Desired
It 5-10
–0.5
0
0.5
y [m]



Desired position
CONTROL
Measured position

EXPERIMENTAL RESULTS

Learned input



QUADROCOPTER SLALOM LEARNING

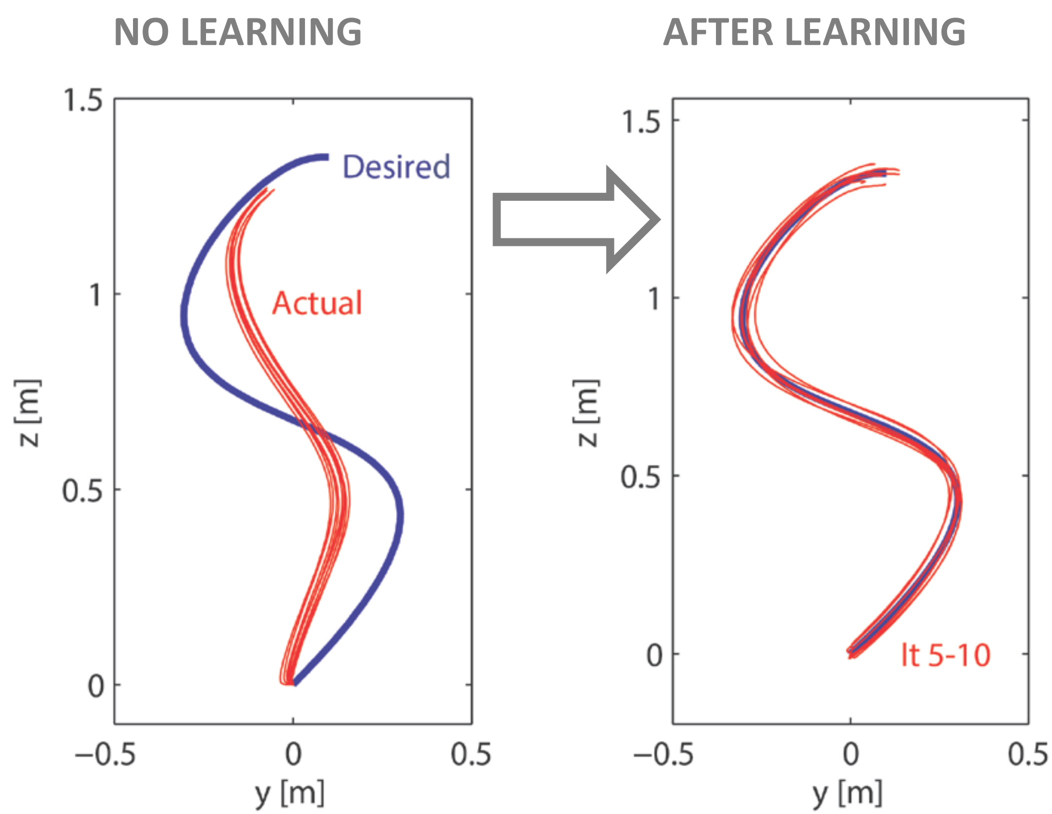
- http://www.youtube.com/watch?v=zHTCsSkmADo

A | CONCLUSIONS

OBJECTIVE Precise tracking of a finite-time output trajectory

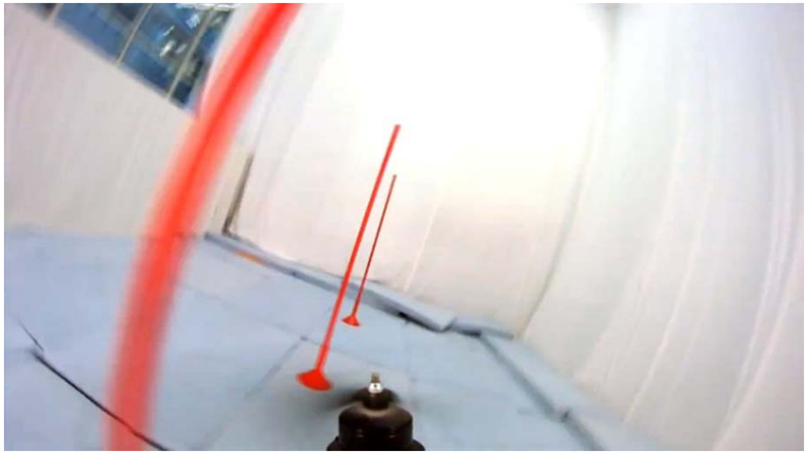
LEARNING Repeated operation, adaptation of full input trajectory

- Learning algorithm combines *model data* with *experimental data*
- Convergence in around 5-10 iterations

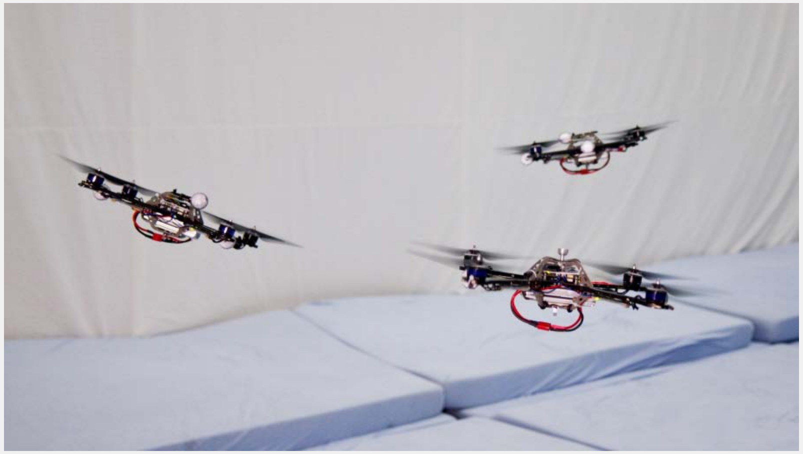


TWO APPLICATION SCENARIOS

A| High-performance slalom racing



B| Coordinated flight synchronized to music



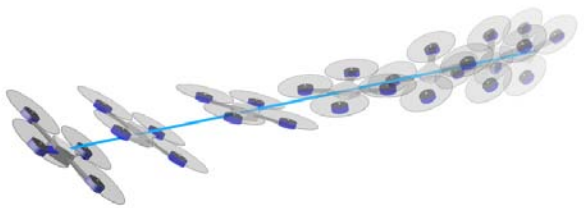
Motivating and demonstrating the developed **trajectory planning** and **trajectory following and learning** algorithms.

Dancing Quadrocopters

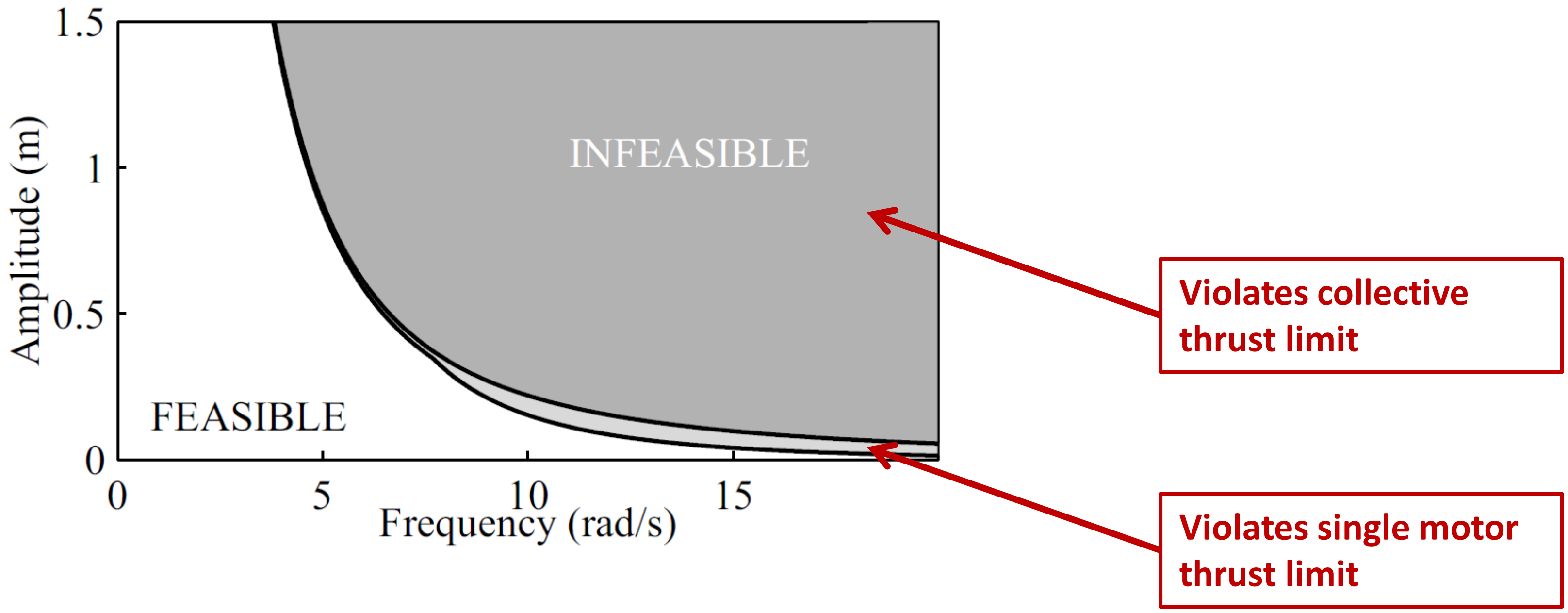
Rise Up

Side-to-side motion.

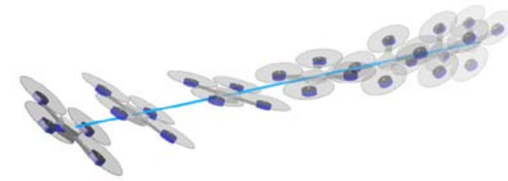
$$s_d(t) = \begin{bmatrix} x_d(t) \\ y_d(t) \\ z_d(t) \end{bmatrix} = \begin{bmatrix} A\cos(\Omega t) \\ 0 \\ 0 \end{bmatrix}.$$



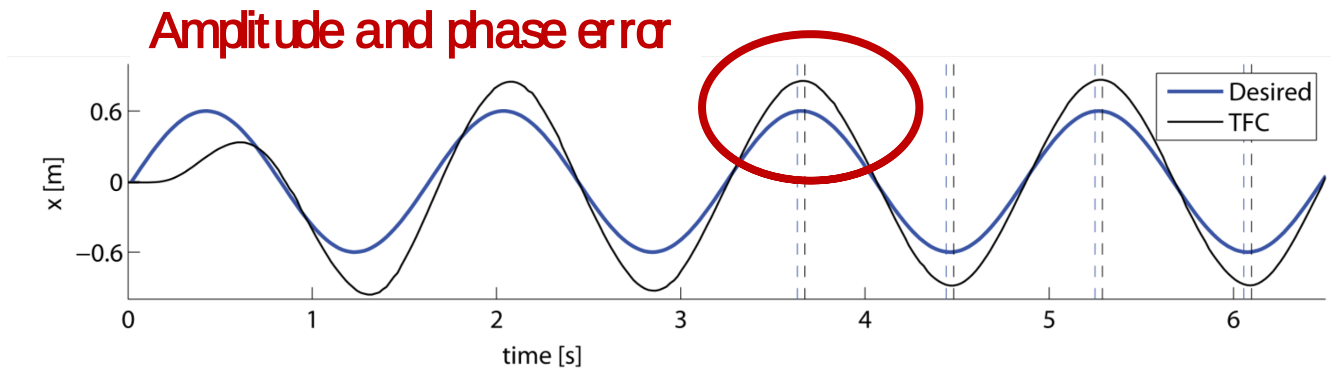
Feasibility.



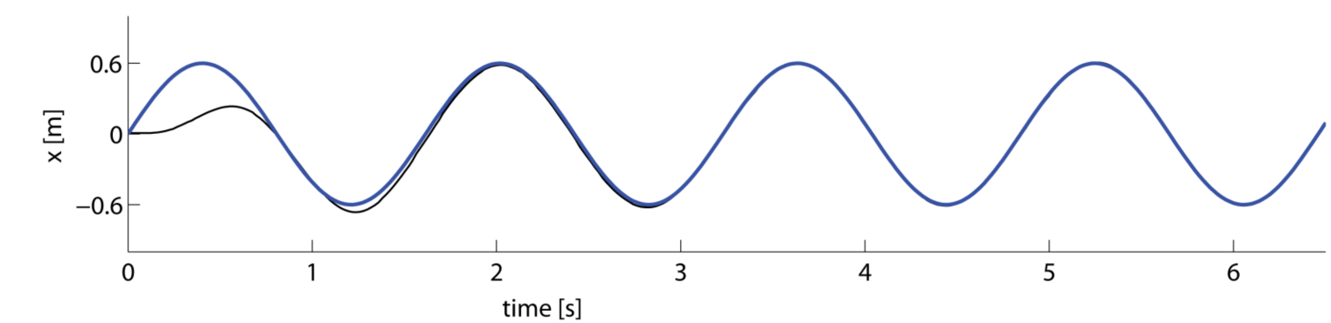
B | TRAJECTORY LEARNING



PURE FEEDBACK



WITH LEARNED CORRECTION FACTORS



OBJECTIVE Precise tracking of periodic motions

METHOD Dedicated identification routine performed prior to flight performance, adaptation of *a few input parameters*

B | TRAJECTORY PLANNING

OBJECTIVE Smooth, collision-free transitions between periodic motions

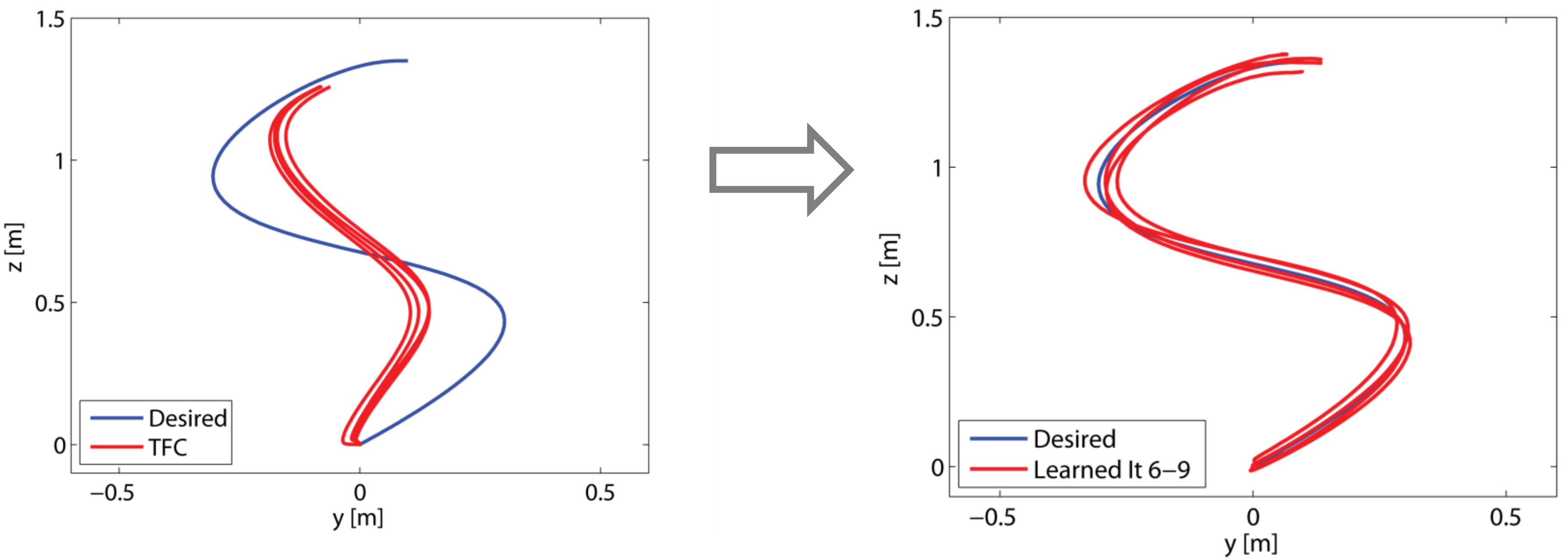
METHOD Sequential convex programming, online calculation

- Uses very simplified model (linear, decoupled directions) and approximate constraints
- Minimize energy
- Guarantees *smooth transitions*: continuous in accelerations (= no jumps in attitude)

- http://www.youtube.com/watch?v=Glvla0nFWHo&feature=c4-overview-vl&list=PLD6AAACCBFFE64AC5

- http://www.youtube.com/watch?v=7r281vgfotg&feature=c4-overview-vl&list=PLD6AAACCBFFE64AC5

Controls and learning enable behavior that would NOT be possible otherwise.



TORONTO


Winnipeg
Gulf of St Lawrence
North Dakota
Montana
Minnesota
New Brunswick
Prince Edward Island
Montreal
Nova Scotia
South Dakota
Wisconsin
Maine
Idaho
Wyoming
Michigan
Toronto
Vermont
New York
New Hampshire
Chicago
Iowa
Nebraska
Illinois
Pennsylvania
Massachusetts
Ohio
Nevada
United States
New York
Rhode Island
Utah
Indiana
Colorado
Kansas
Missouri
West Virginia
Connecticut
Kentucky
Virginia
New Jersey
Tennessee
North Carolina
Oklahoma
Arkansas
Delaware
Arizona
Maryland
New Mexico
South Carolina
Dallas
Mississippi
District of Columbia
Phoenix
Alabama
San Diego
Texas
Georgia
Louisiana

APPLICATIONS

PrecisionHawk

- Environmental monitoring
- Precision agriculture

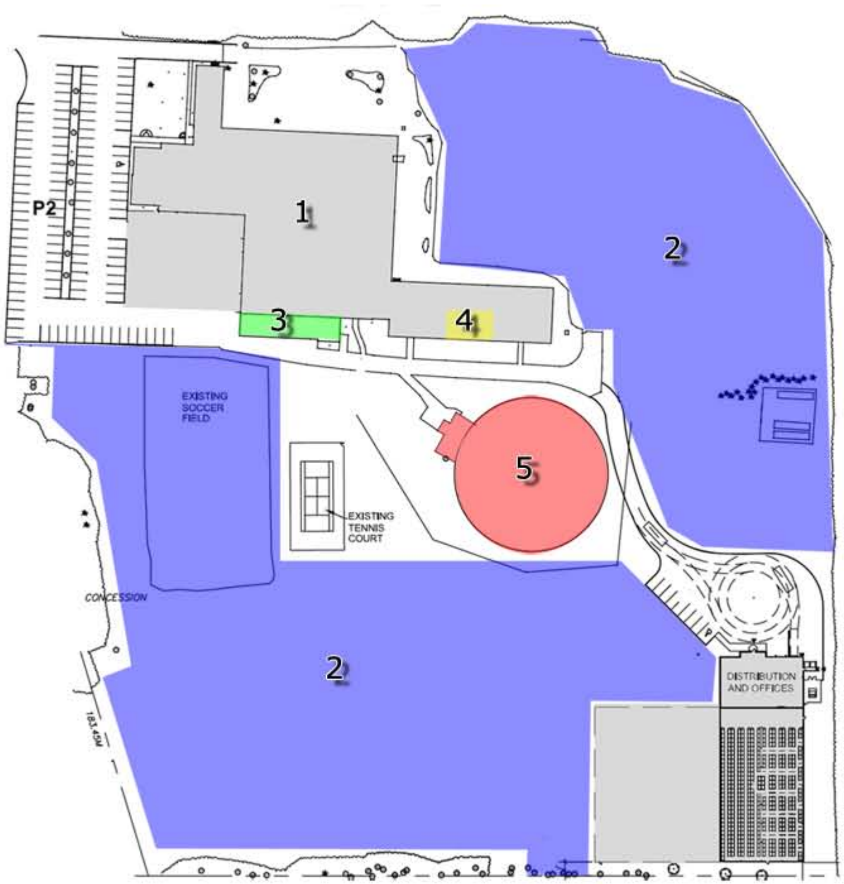
Aeryon Inc.

- Aerial imaging

MDA

- Repeated measurements

TORONTO



1 - UTIAS
2 - Outdoor Robotics Testbed
3 - Robotics Machine Shop
4 - Indoor Robotics Testbed (Vicon)
5 - MarsDome

THANK YOU

Follow us!

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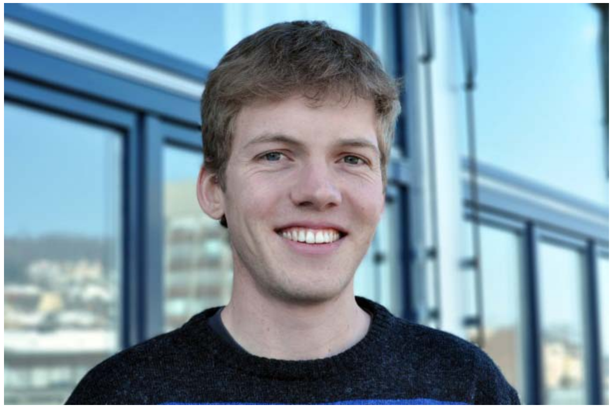
THANK YOU



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