Iterative Learning of Feed-Forward Corrections for High-Performance Tracking

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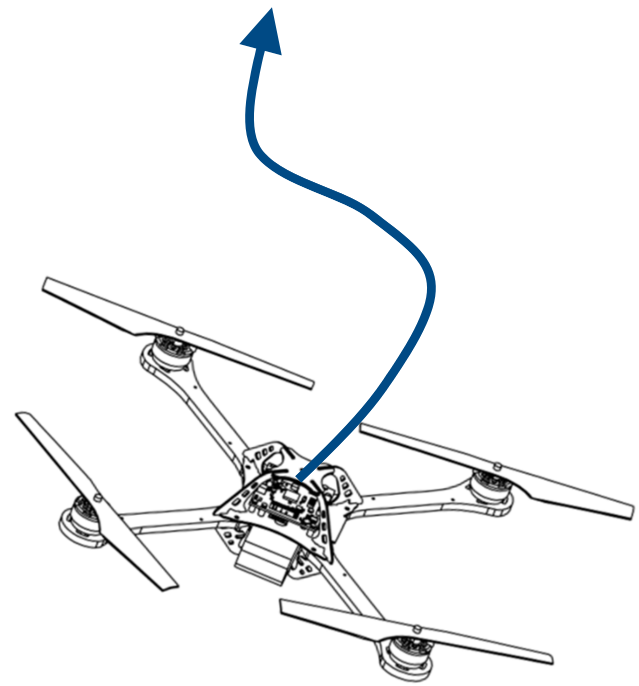
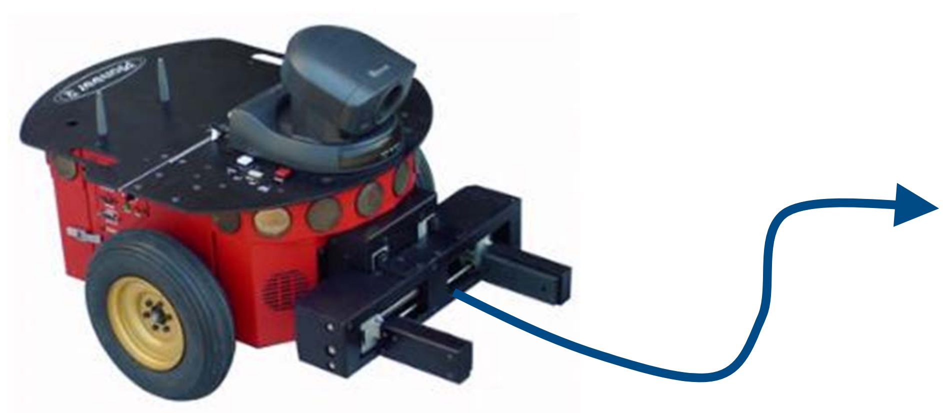
GOAL – Precise tracking of a desired output trajectory





GOAL – Precise tracking of a desired output trajectory

Example: Quadrotor vehicle

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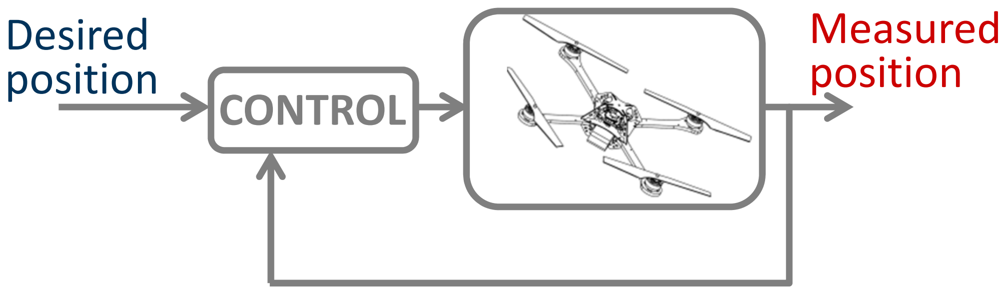
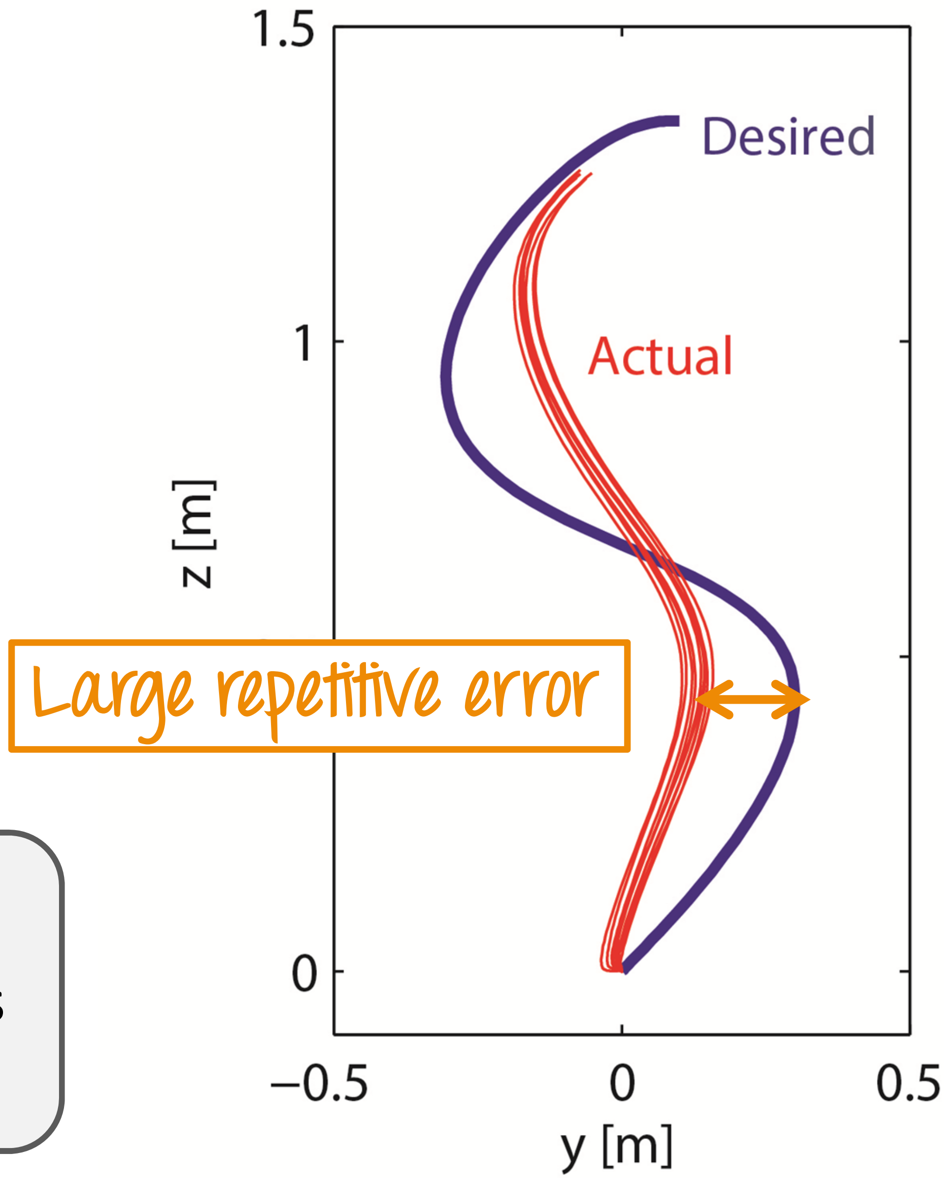
Example: Quadrotor vehicle

Typical setup: Feedback control



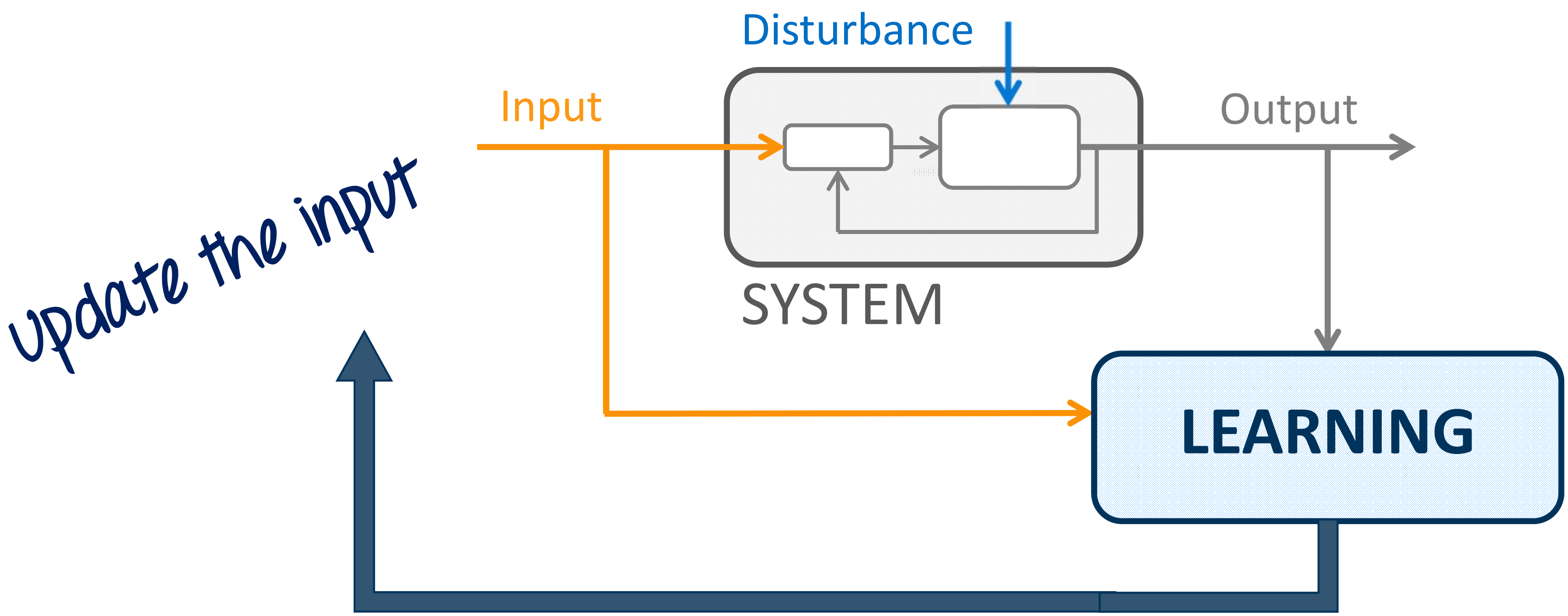
Limitations of feedback control:

Disturbances and unmodelled dynamics (non-zero mean)



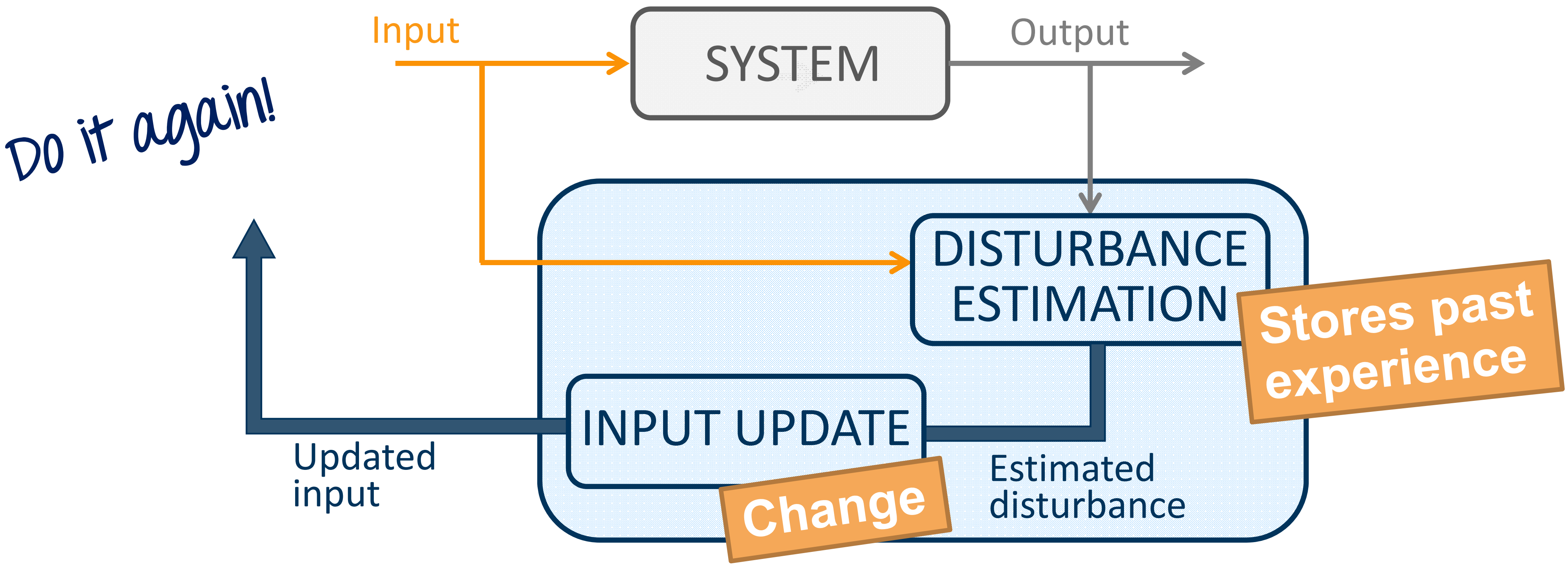
LEARNING APPROACH

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



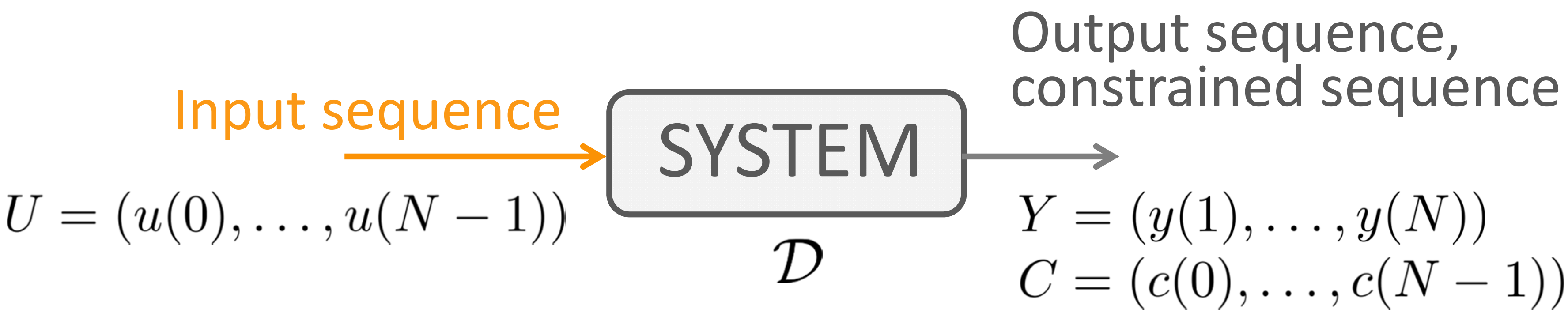
Potential: Acausal action, anticipating repetitive disturbances.

LEARNING APPROACH



1. Dynamics model (here: from numerical simulation)
2. Disturbance estimation*
3. Update of input trajectory*

* Angela P. Schoellig, Fabian L. Mueller, Raffaello D'Andrea, "Optimization-based iterative learning for precise quadrocopter trajectory tracking," Autonomous Robots, 2012



Prerequisites:

- **Coarse model** $\mathcal{D} : U \rightarrow (Y, C)$
- **Desired output trajectory** Y^*
  with corresponding nominal input $(Y^*, C^*) = \mathcal{D}(U^*)$

1 | DYNAMICS MODEL

Define:

- **Linear mapping** from *input deviations* to *changes in output and constrained variables*:

$$\boxed{\mathrm{y} = F\,\mathrm{u}\,, \qquad \mathrm{c} = L\,\mathrm{u}}$$

$$\mathrm{u} = U - U^*,$$
$$\mathrm{y} = Y - Y^*, \quad \mathrm{c} = C - C^*$$

From numerical dynamics simulation:

- Obtain F, L by running $2N$ identification runs
  - Apply $U_{i+} = (u^*(0), \ldots, u^*(i) + \Delta u, \ldots, u^*(N-1)) \quad \rightarrow (Y_{i+}, C_{i+})$
  - Obtain $F(:,i) = (Y_{i+} - Y^*)/\Delta u$
    $L(:,i) = (C_{i+} - C^*)/\Delta u$ ← ith column

1 | ITERATION-DOMAIN MODEL

For each trial $j,\ j \in \{1,\, 2,\, \ldots\}$,

$$\mathrm{y}_j = F\,\mathrm{u}_j + \mathrm{d}_j + \mu_j.$$

Recurring disturbance d_j**.**
Unknown. Only small changes between iterations:

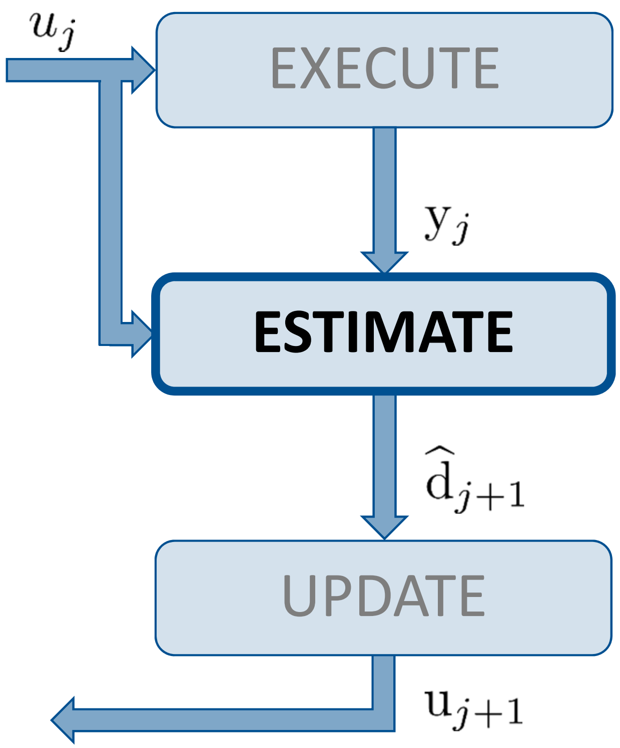
$$\mathrm{d}_{j+1} = \mathrm{d}_j + \omega_j.$$

$\mu_j, \omega_j -$ trial-uncorrelated, zero-mean Gaussian noise

Noise μ_j**.**
Unknown. Changing from iteration to iteration.

From trial to trial our knowledge about d_j improves.

ESTIMATION



UPDATE OF DISTURBANCE ESTIMATE

via **Kalman filter** in the iteration domain:

Prediction step:

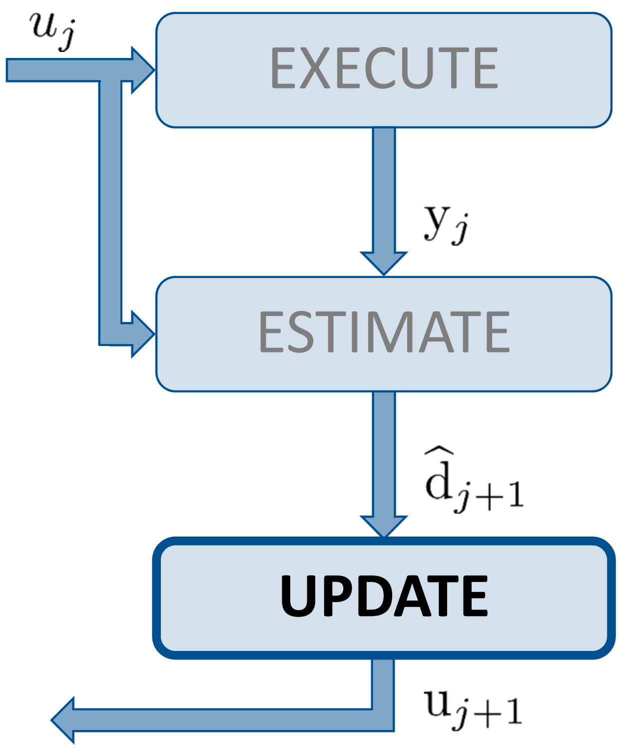
$$\mathrm{d}_{j+1} = \mathrm{d}_j + \omega_j .$$

Measurement update step:

$$\mathrm{y}_j = F\,\mathrm{u}_j + \mathrm{d}_j + \mu_j .$$

→ Obtain $\widehat{\mathrm{d}}_{j+1}$.

INPUT UPDATE



INPUT UPDATE via **convex optimization:**

minimizes the expected tracking error in the next trial:

$$\mathrm{E}\left[\mathrm{y}_{j+1} | \text{all past measurements}\right] = F\,\mathrm{u}_{j+1} + \widehat{\mathrm{d}}_{j+1}.$$

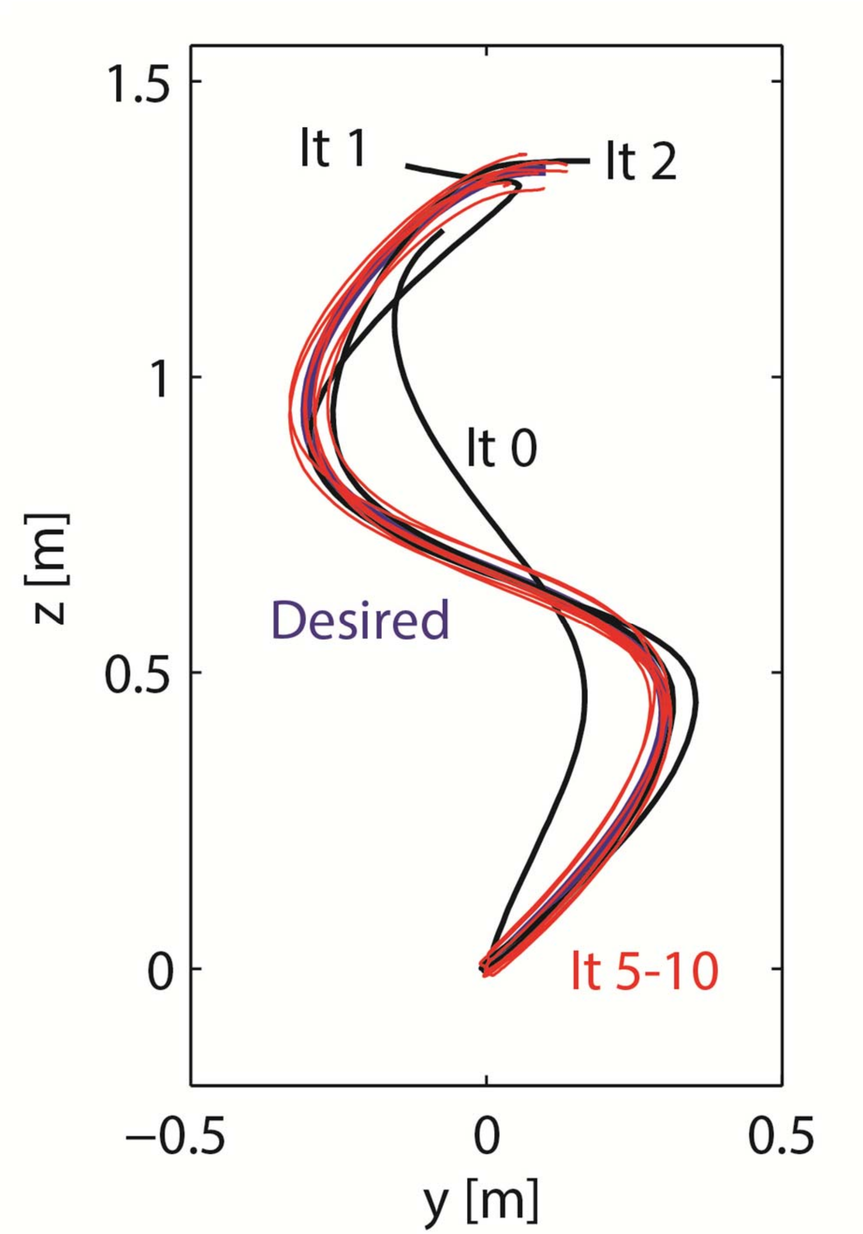
$$\min_{\mathrm{u}_{j+1}} \left\| F\,\mathrm{u}_{j+1} + \widehat{\mathrm{d}}_{j+1} \right\|_p \qquad p \in \{1,\, 2,\, \infty\}$$

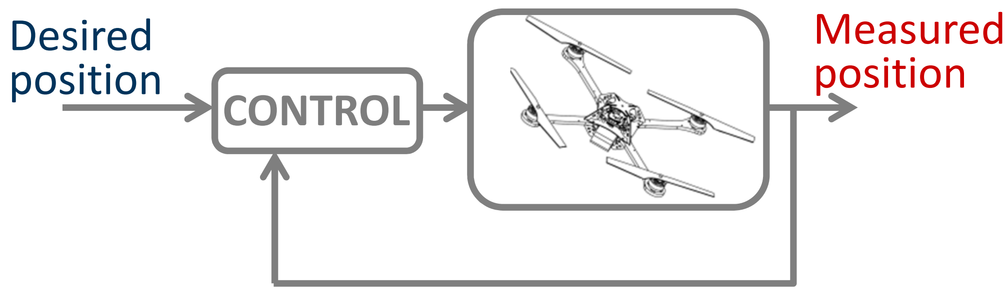
subject to

$$L\,\mathrm{u}_{j+1} \preceq \mathrm{c}_{\max}$$

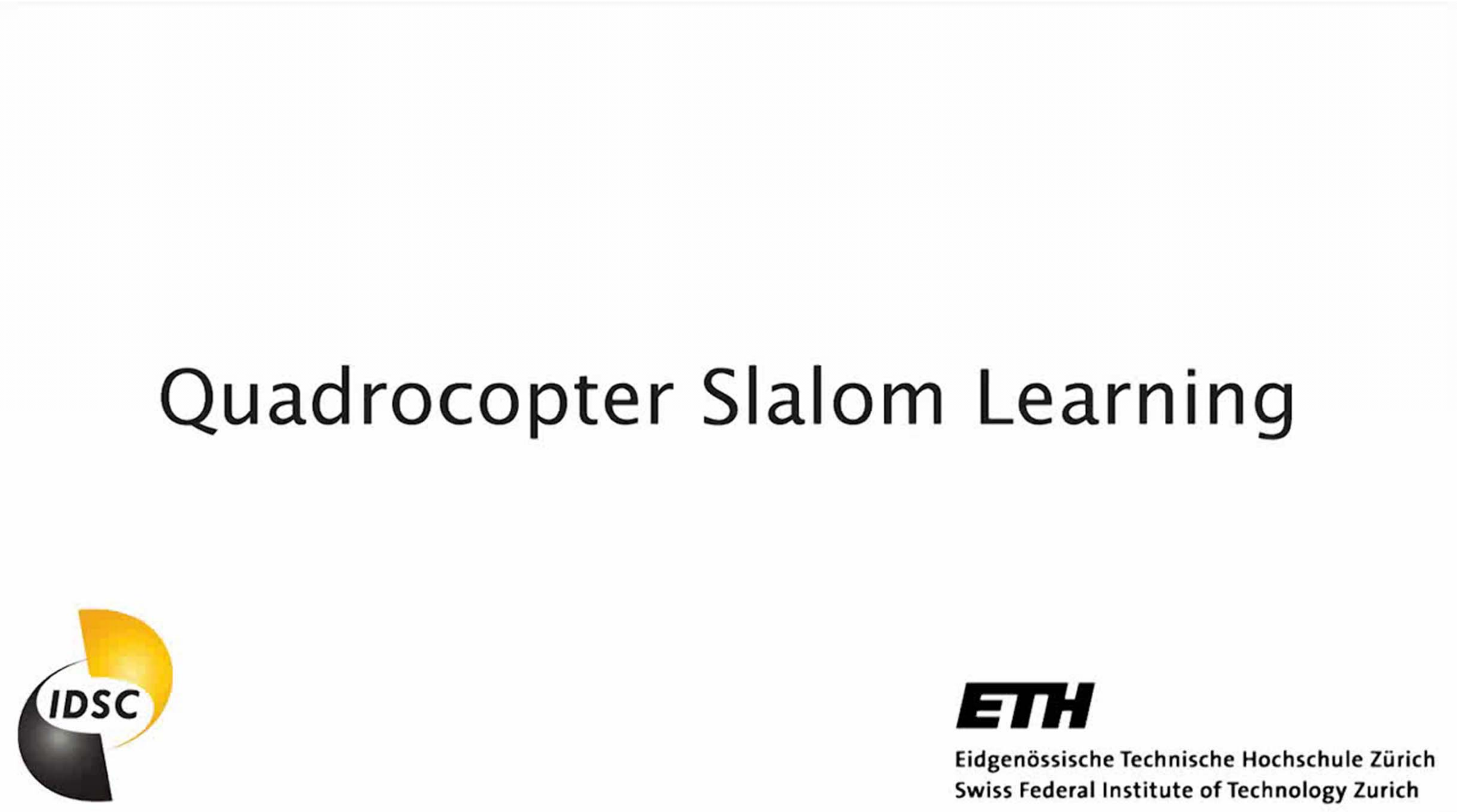
Obtain u_{j+1}.

EXPERIMENTAL RESULTS



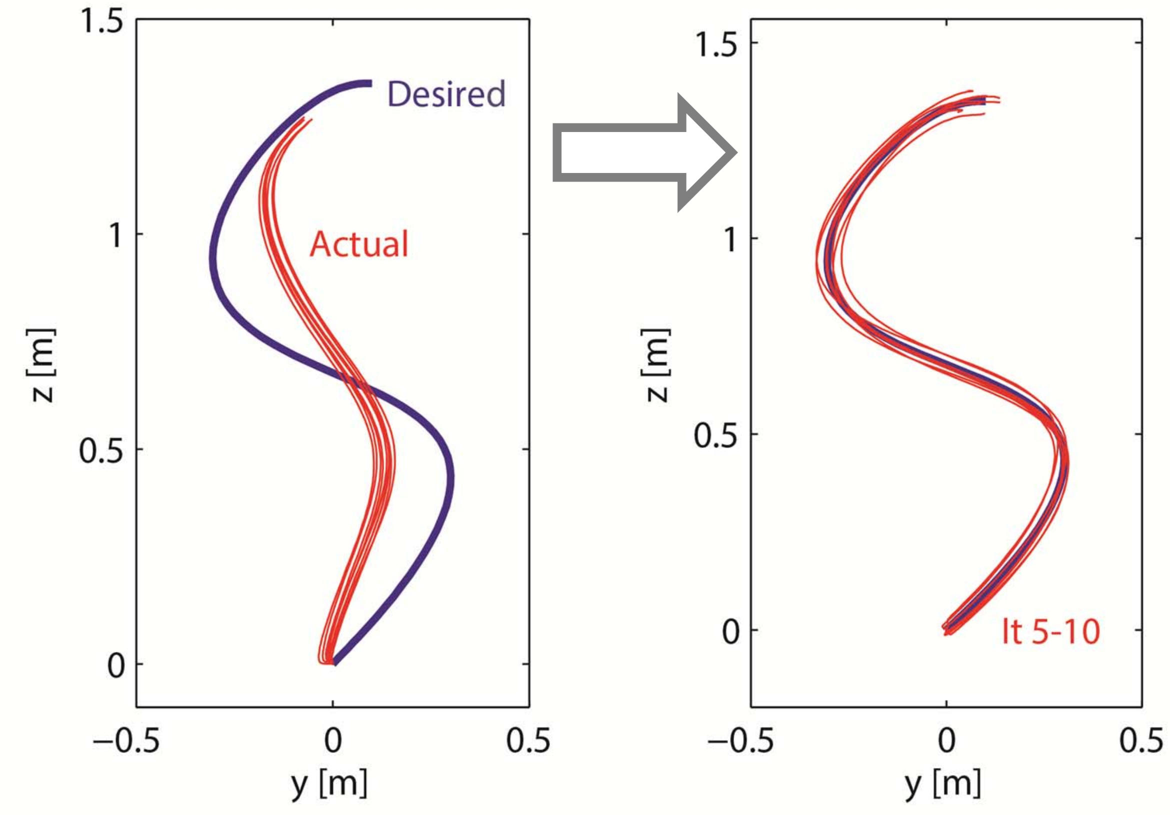


VIDEO: https://youtu.be/zHTCsSkmADo?list=PLC12E387419CEAFF2



CONCLUSIONS

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



Repetitive error components can be effectively compensated for by learning from past data.

Result is an **improved tracking performance**.