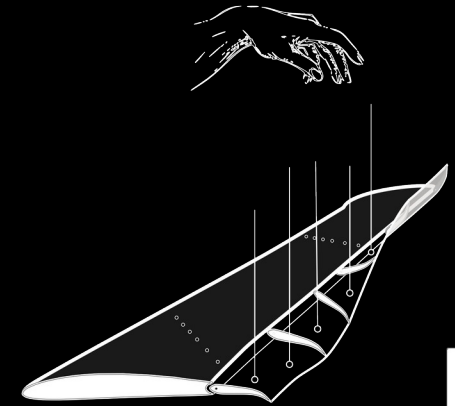


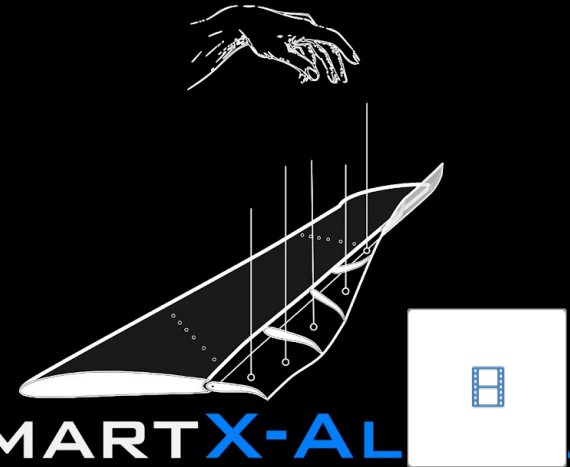
Virtual, ASME 2020 SMASIS, 15 September 2020



Virtual, ASME 2020 SMASIS, 15 September 2020

# Design and Real-Time Implementation of a Vision-Based Adaptive Model-Free Morphing Wing Motion Control Method

Tigran Mkhoyan, Xuerui Wang,  
Coen de Visser, Roeland De Breuker  
Delft University of Technology, Delft, The Netherlands





# Flexible Structures



# Introduction

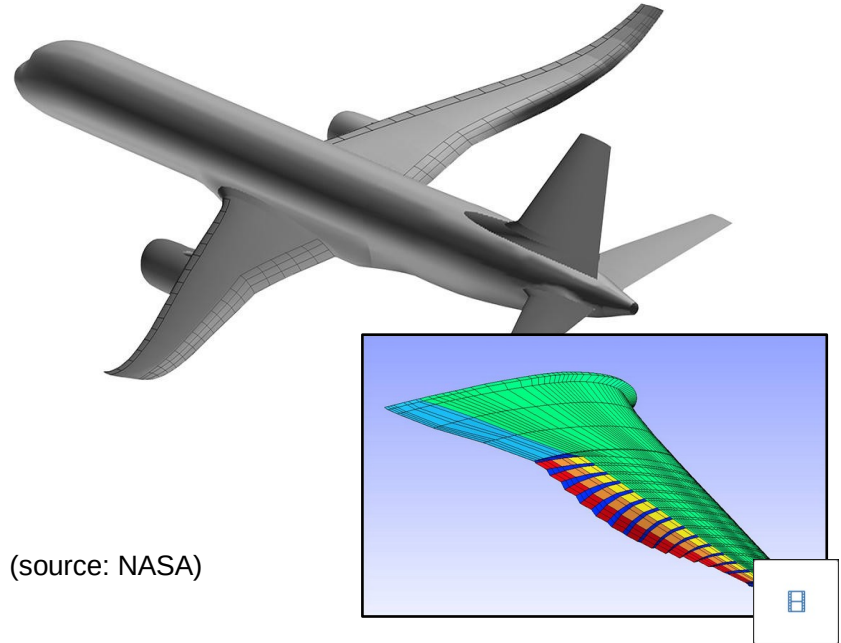
Trend towards flexible configurations:

Adaptive Compliant Trailing Edge



(source: NASA)

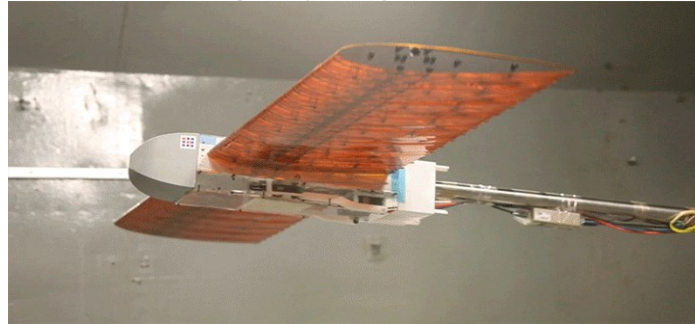
Variable camber continuous trailing edge flap flap



(source: NASA)

# Applications: slender flexible (morphing) aircraft

**Cellular morphing wing**



(source: NASA AMES/MIT)

**HALE solar power aircraft**



(source: NASA)

**Facebook drone aquila**



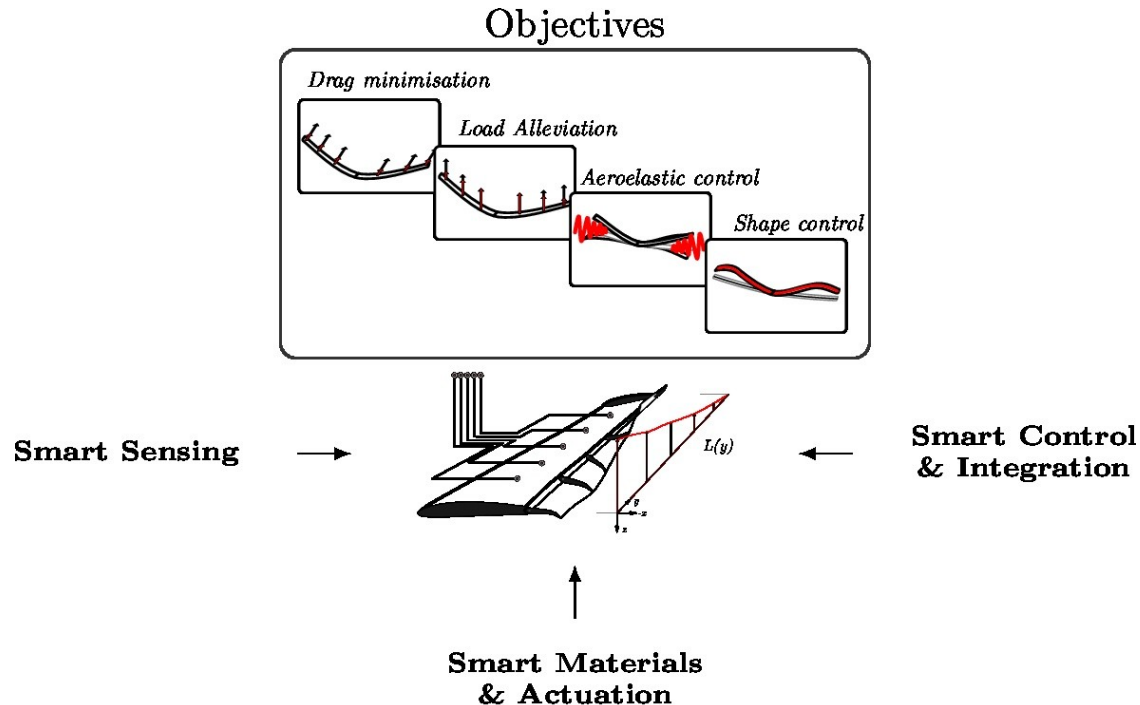
(source: Facebook)

# Smart-X

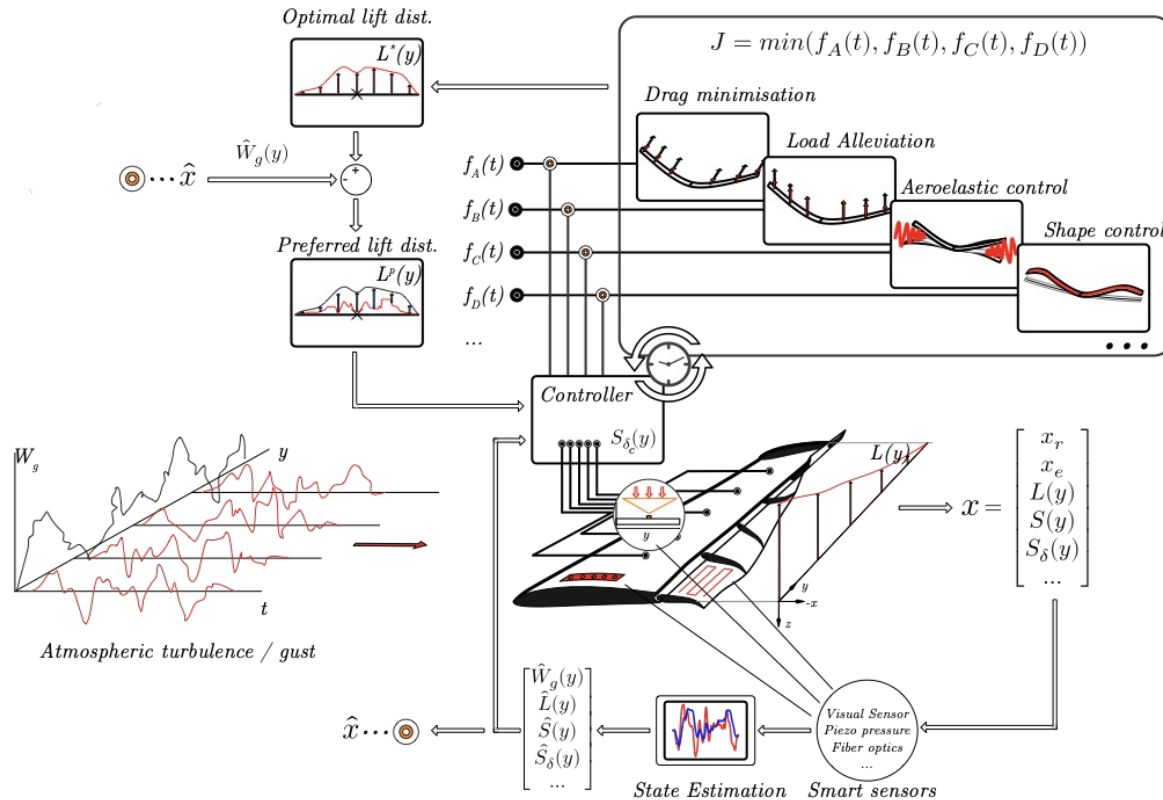


# Goal: the Smart Morphing Wing

How can we use multidisciplinary integration of novel control laws, sensing methods, and actuation mechanism for real-time, in-flight, multi-objective optimisation of actively morphing wing?



# Real-time multi-objective performance optimisation



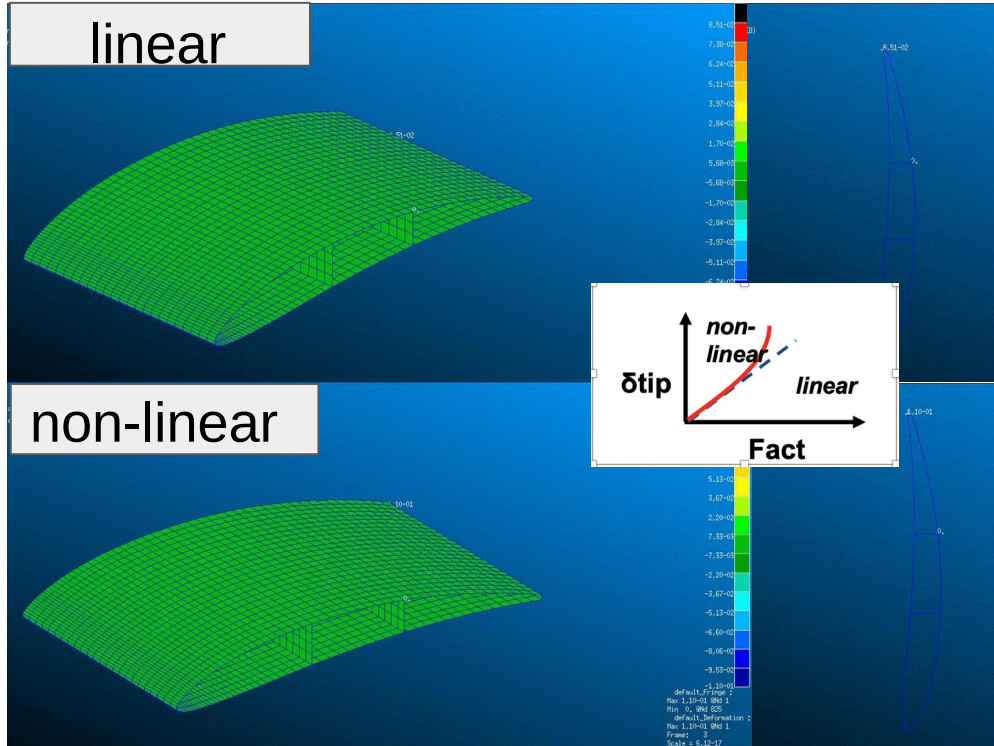
# Challenges Morphing Structures

# Challenges control design morphing: non-linearity

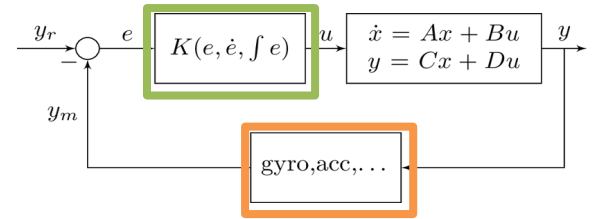
actuator force non-linear control effectiveness mapping:

sensor

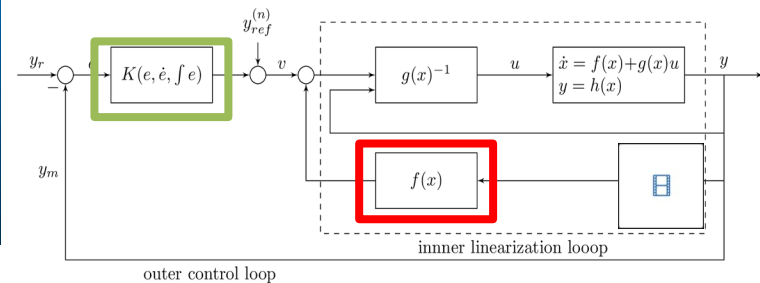
PID controller



Typical: Linear + PID

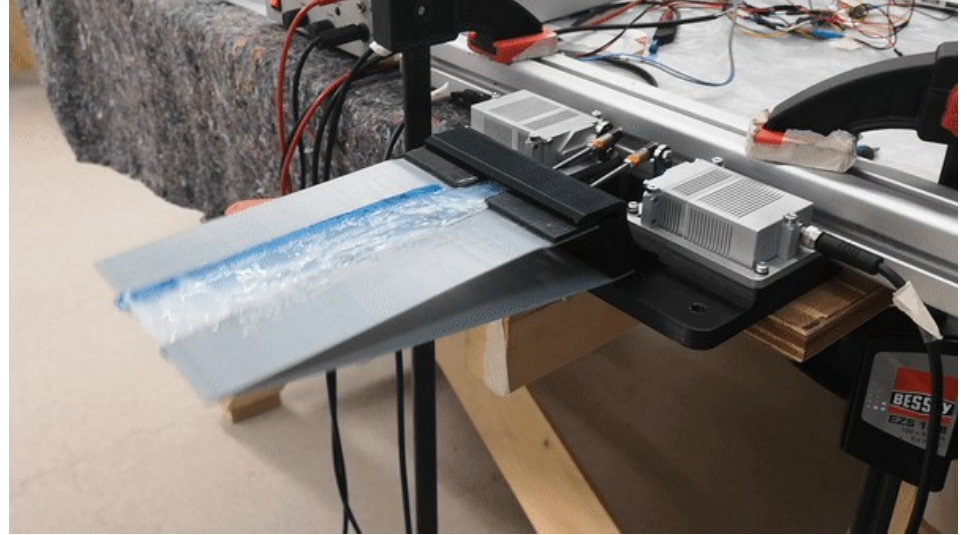
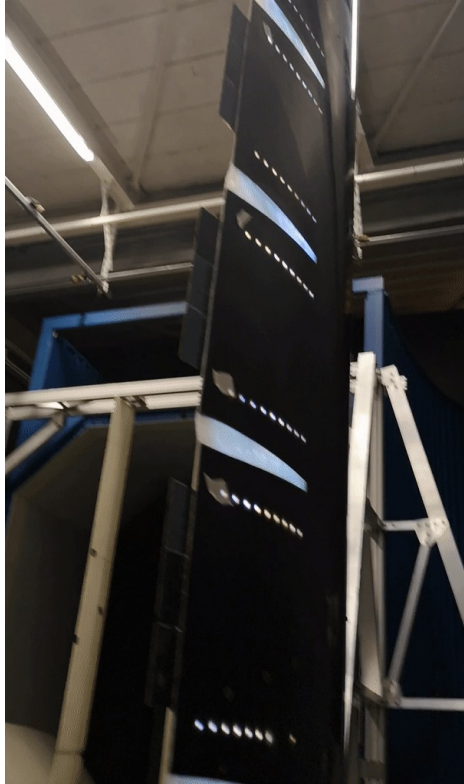


non-linear dynamics (act + model)





# Smart-X morphing in action



# Gaps in Literature: Control & Sensors

Current



Needed



Current

Largely linear and slow	Fast, accurate non-linear models	Non-linear CA method for IBS → IBSCA	Non-Linear CA methods active research area
Large $N_{states}$ → Empiric ROM	<i>Justified</i> ROM for control	Justified model reduction (control)	Large $N_{states}$ slow for RT control models
Design methodology passive (tayloring)	Design methodology active (control)	Lyapunov stability distributed coupled systems	Stability of distributed coupled systems unsolved
Quasi steady aerodynamics (2D models)	Unsteady aerodynamics (2D and 3D models)	Model free adaptive sensing techniques	Novel control methods sensors dependent
Aeroelastic Modelling		Control & Sensors	

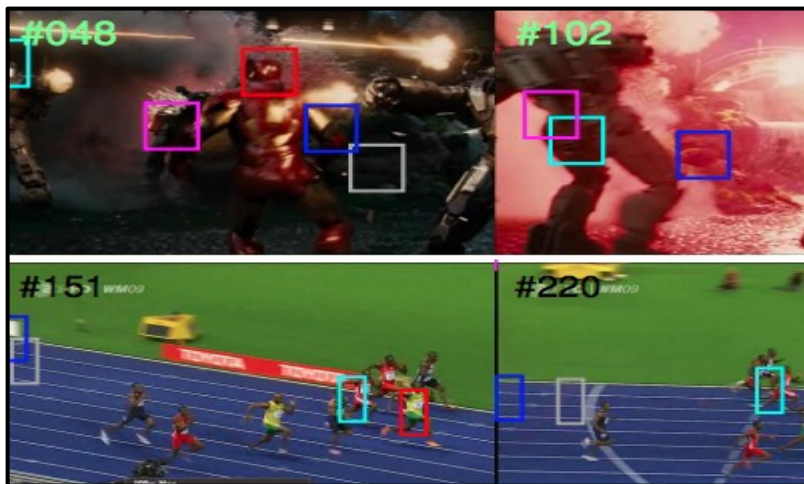


# VISUAL TRACKING

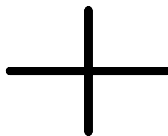


# Proposed Concepts: Control & Sensors

Visual tracking

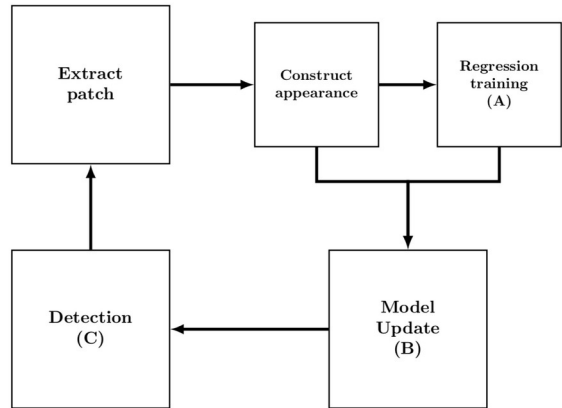


Kalman Filter



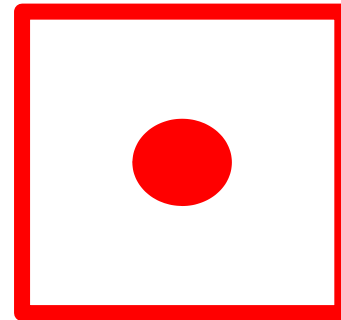
# Visual tracking KCF-Kalman couple

- Novel method for monitoring wing displacements and loads real-time with simple camera feed (e.g. mounted in the fuselage)
- Combines speed of KCF (Kernelized Correlation filter) with robustness and prediction of the KF (Kalman Filter)

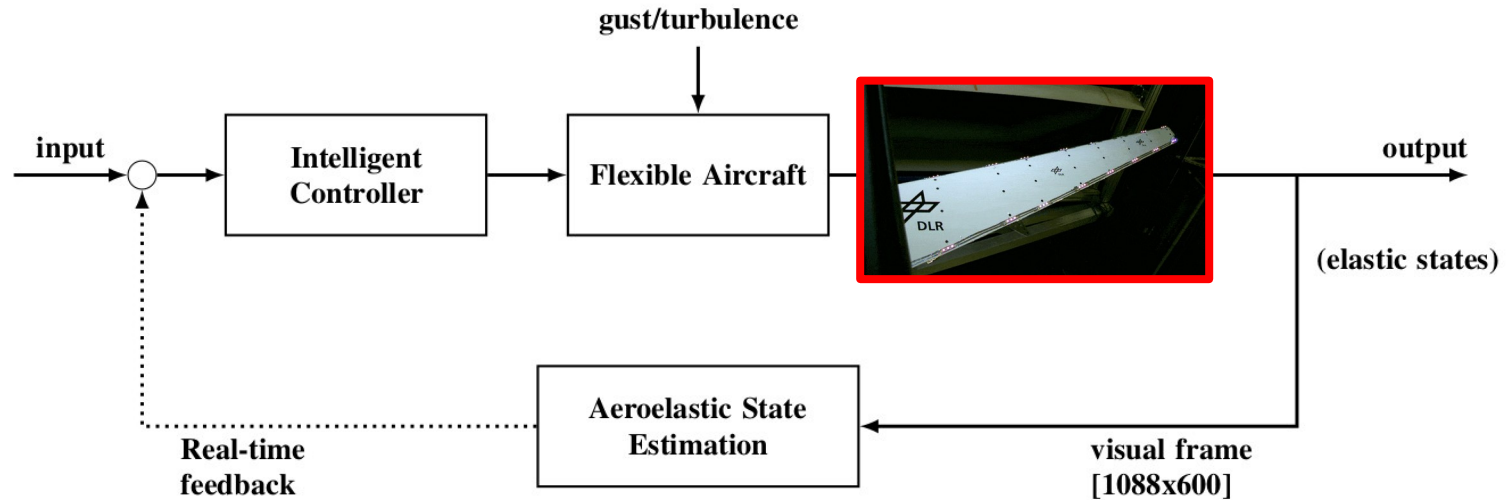


+

KF (*prediction*)



# A Simplified Control diagram Visual Tracking

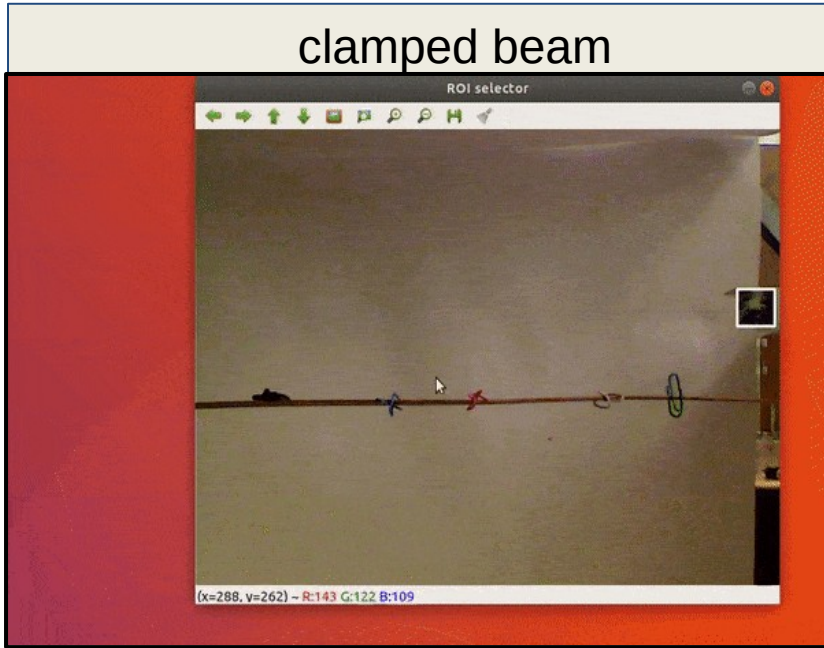


**Question:** *Can we provide aeroelastic feedback with alternative sensors for Real-time control?*

**Purpose:** *Investigate how to eliminate dependency on both model  $f(x)$  control effectiveness  $g(x)$*

# Visual tracking KCF-Kalman couple

clamped beam

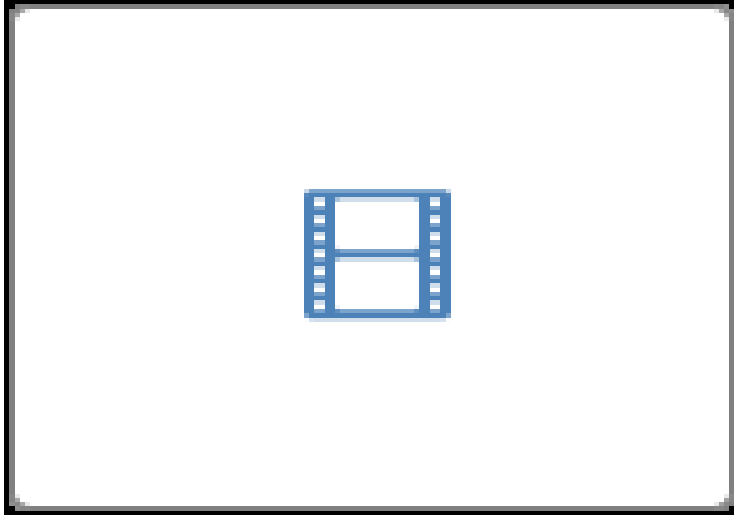


actual wing wt



# Visual tracking KCF-Kalman couple

clamped beam

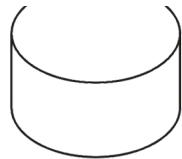
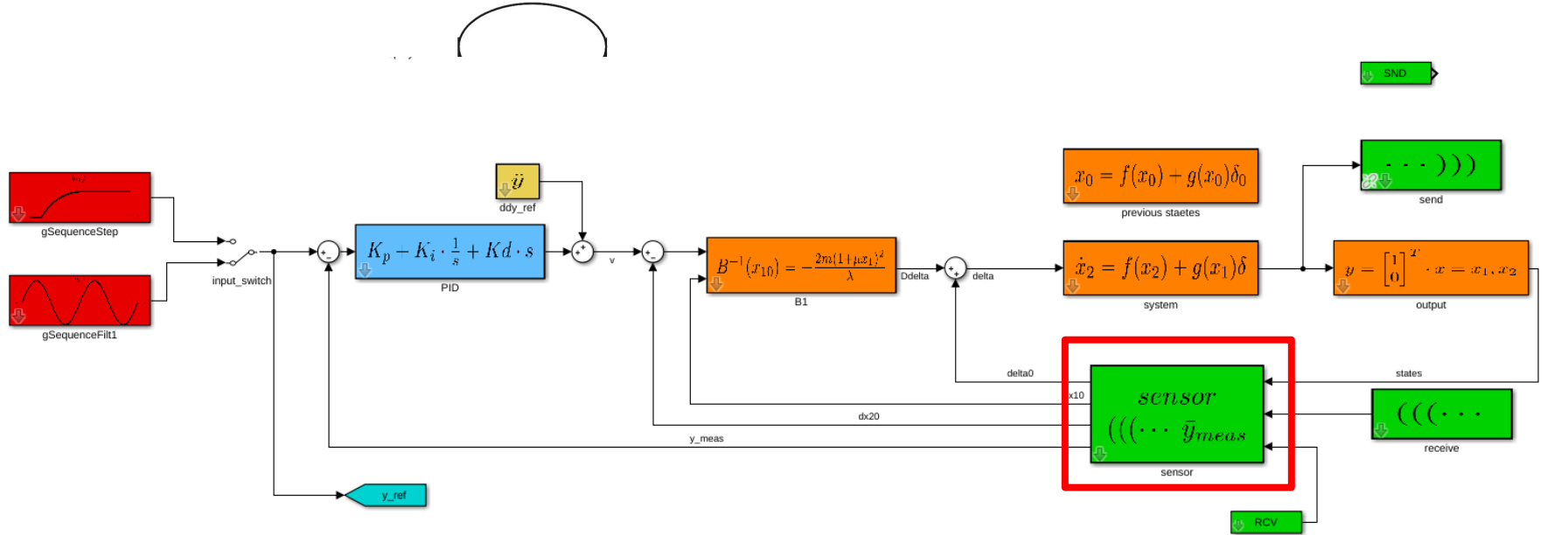


actual wing wt



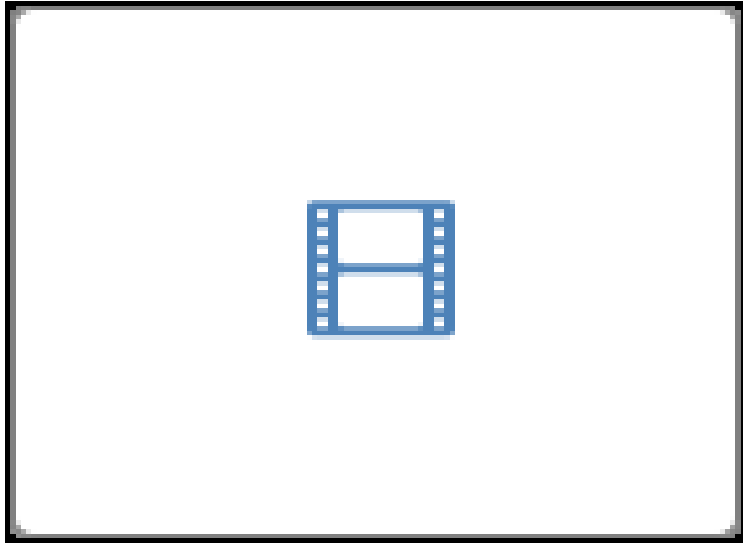


# Control problem: suspended magnet

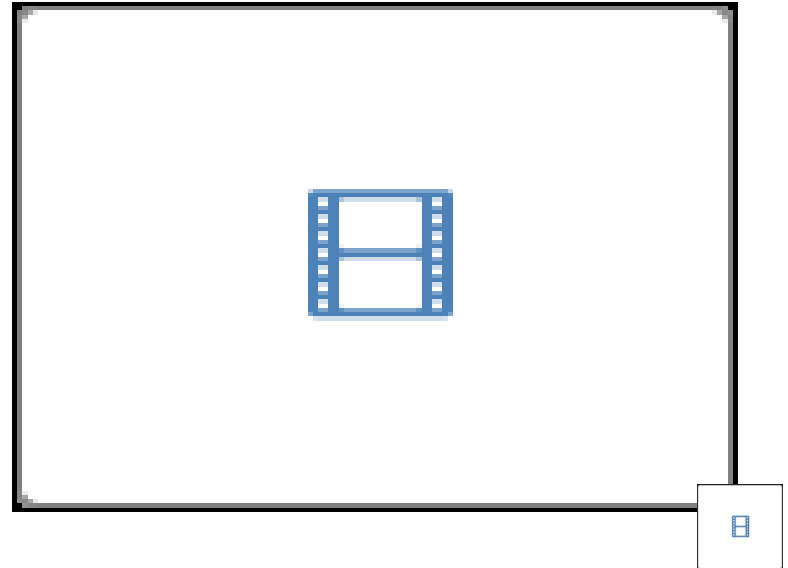


# Visual tracking control feedback

Closed loop: Motion feedback

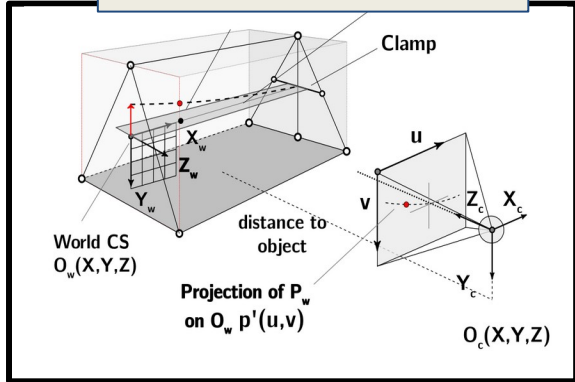


Freehand: Tracking actuator motion

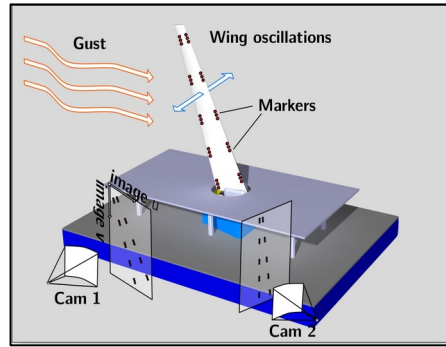


# Experiments in wind tunnel and flight test

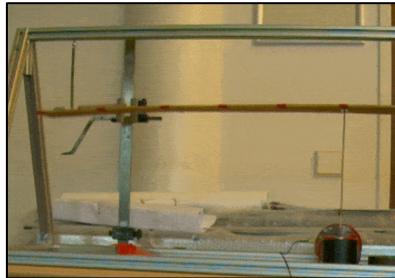
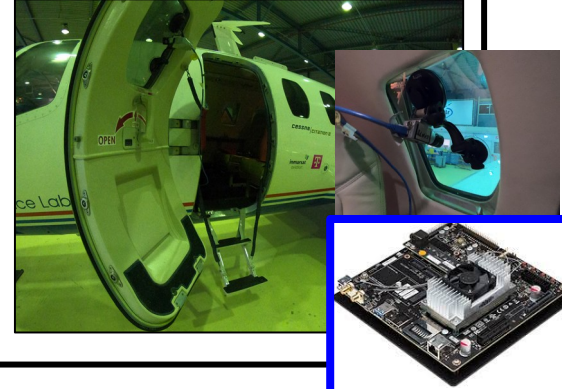
Single camera clamped beam:



WT test stereo setup:

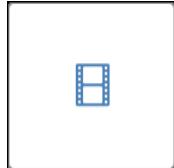
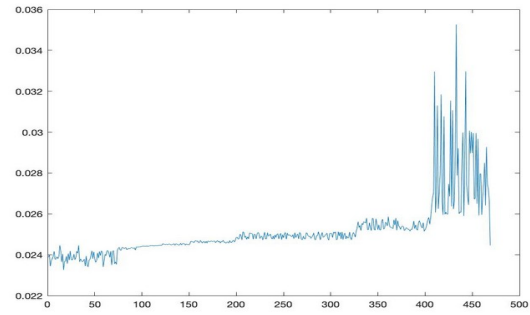
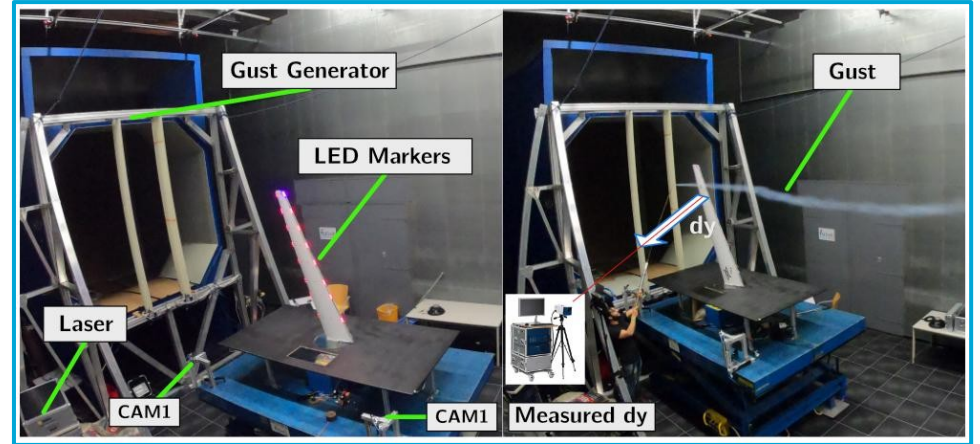
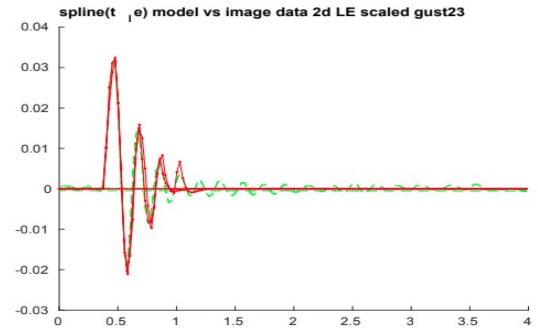
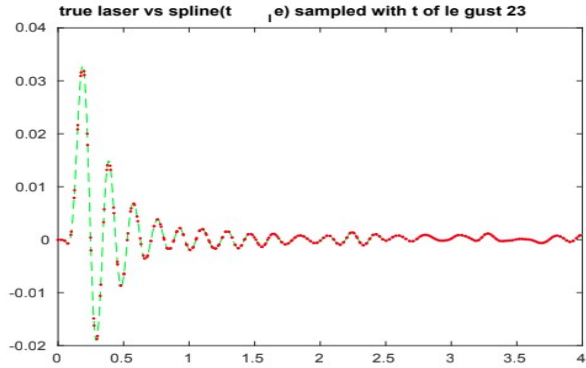


FT Cessna Citation



# Adaptive Visual Tracking experimental data

Laser data sampled at non-uniform time step of camera:



# Kalman Filter: Adding Dynamics to visual motion:

$$x(t+h) = x(t) + f'(x(t))h$$

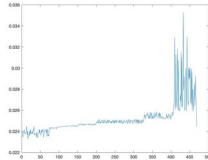
**Kalman Filter (KF):** Predicting linear motion

$$x_k = x_{k-1} + \dot{x}_{k-1}h$$

$$y_k = y_{k-1} + \dot{x}_{k-1}h$$

$$\dot{y}_k = \dot{y}_{k-1} + \ddot{y}_{k-1}h$$

**Extended KF (EKF):** Non-linear motion, non-uniform timestep



The general differential equation is given as:

$$\ddot{y}(t) = -\frac{c}{m}\dot{y}(t) - \frac{k}{m}y(t)$$

In state space form we have:

$$\frac{d}{dt} \begin{bmatrix} y_k \\ \dot{y}_k \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -k/m & -c/m \end{bmatrix} \begin{bmatrix} y_k \\ \dot{y}_k \end{bmatrix}$$

**Augmented (AEKF):** Non-linear motion, time-varying, learn unknown dynamics

$$\ddot{y}(t) = -\frac{c(t)}{m(t)}\dot{y}(t) - \frac{k(t)}{m(t)}y(t)$$

$$\bar{x}_k = \begin{bmatrix} y_k \\ \dot{y}_k \\ K_k \\ c_k \\ m_k \end{bmatrix} = \begin{bmatrix} y_{k-1} + \dot{x}_{k-1}h \\ -K_{k-1}/m_{k-1} \cdot y_{k-1} - (1 - c_{k-1}/m_{k-1}h) \cdot \dot{y}_{k-1} \\ K_{k-1} + 0 \cdot h \\ c_{k-1} + 0 \cdot h \\ m_{k-1} + 0 \cdot h \end{bmatrix} \quad (13)$$

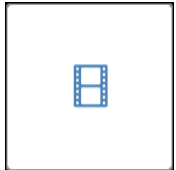
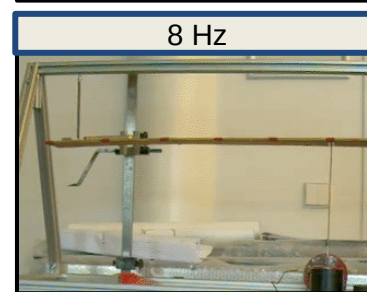
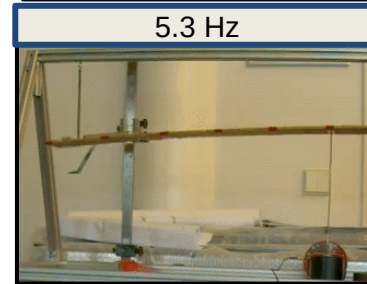
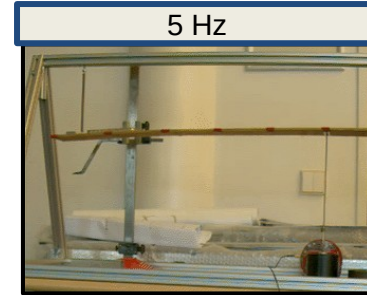
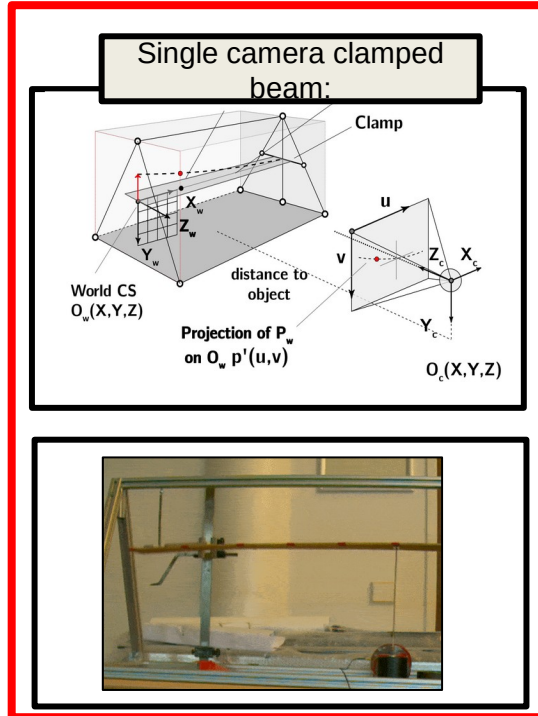


$$J(\bar{x}_k) = \begin{bmatrix} 1 & h & 0 & 0 & 0 \\ -K_{k-1} \cdot m_{k-1}^{-1} & 1 - c_{k-1} \cdot m_{k-1}^{-1} \cdot h & m_{k-1}^{-1} \cdot y_{k-1} \cdot h & -m_{k-1}^{-1} \cdot \dot{y}_{k-1} \cdot h & m_{k-1}^{-2} \cdot c_{k-1} \cdot \dot{y}_{k-1} \cdot h - m_{k-1}^{-2} \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



# Tracking and identification cantilever beam

$$m_s \ddot{q} + c_s(q) \dot{q} + k_s(q) q = d_s + F_u$$



# CONTROL DESIGN



# Control Design

- ❖ System dynamics

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{G}(\mathbf{x})\mathbf{u} + \mathbf{d}_x \quad \mathbf{y} = \mathbf{h}(\mathbf{x})$$

- ❖ Input-output dynamics

$$\mathbf{y}^{(r)} = \boldsymbol{\alpha}(\mathbf{x}) + \mathcal{B}(\mathbf{x})\mathbf{u} + \mathbf{d}$$

Assume the vector relative degree is constant and known, and the corresponding internal dynamics are stable.

- ❖ Sliding variable

$$\boldsymbol{\sigma} = \mathbf{y} - \mathbf{y}_c$$

- ❖ R-th order sliding set

$$\mathcal{S}^r = \{\mathbf{x} | \sigma_i(\mathbf{x}) = \dot{\sigma}_i(\mathbf{x}) \dots = \sigma_i^{(r_i-1)}(\mathbf{x}) = 0, i = 1, \dots, m\}$$

Motions on  $\mathcal{S}^r$  is called the r-th order sliding mode with respect to  $\boldsymbol{\sigma}$



# Incremental Sliding Mode Control

- ❖ Incremental dynamic equation [1]

First-order Taylor series expansion around the condition at , denoted by subscript 0

$$\mathbf{y}^{(r)} = \mathbf{y}_0^{(r)} + \mathcal{B}(\mathbf{x}_0)\Delta\mathbf{u} + \Delta\mathbf{d} + \left. \frac{\partial[\boldsymbol{\alpha}(\mathbf{x}) + \mathcal{B}(\mathbf{x})\mathbf{u}]}{\partial\mathbf{x}} \right|_0 \Delta\mathbf{x} + \mathbf{R}_1$$

- ❖ Sensor-based control input structure

$$\Delta\mathbf{u}_{\text{indi-}s} = \bar{\mathcal{B}}^{-1}(\mathbf{x}_0)(\boldsymbol{\nu}_n + \boldsymbol{\nu}_s + \mathbf{y}_c^{(r)} - \mathbf{y}_0^{(r)})$$

Designs the control increments in

$$\mathbf{u}_{\text{indi-}s} = \mathbf{u}_{\text{indi-}s,0} + \Delta\mathbf{u}_{\text{indi-}s}.$$

Uses the latest sampled information

- ❖ Closed-loop sliding variable dynamics

$$\begin{aligned} \boldsymbol{\sigma}^{(r)} &= \mathbf{y}^{(r)} - \mathbf{y}_c^{(r)} = \mathbf{y}_0^{(r)} + \bar{\mathcal{B}}(\mathbf{x}_0)\Delta\mathbf{u}_{\text{indi-}s} + \boldsymbol{\varepsilon}_{\text{indi-}s} - \mathbf{y}_c^{(r)} \\ &= \boldsymbol{\nu}_n + \boldsymbol{\nu}_s + \boldsymbol{\varepsilon}_{\text{indi-}s} \end{aligned} \quad (9)$$

Achieves r-th order sliding motion

- ❖ Perturbation term

$$\boldsymbol{\varepsilon}_{\text{indi-}s} = \left. \frac{\partial[\boldsymbol{\alpha}(\mathbf{x}) + \mathcal{B}(\mathbf{x})\mathbf{u}_{\text{indi-}s}]}{\partial\mathbf{x}} \right|_0 \Delta\mathbf{x} + \mathbf{R}_1|_{\mathbf{u}=\mathbf{u}_{\text{indi-}s}} + (\mathcal{B} - \bar{\mathcal{B}})|_0 \Delta\mathbf{u}_{\text{indi-}s} + \Delta\mathbf{d}$$



# Incremental Sliding Mode Control

## ❖ Super twisting sliding mode disturbance observer

auxiliary sliding variable

$$s = \sigma^{(r-1)} - \int \nu_n$$

Closed-loop dynamics

$$\dot{s} = \nu_s + \epsilon_{\text{indi-}s}$$

Observer design

$$\nu_s = -\lambda|s|^{1/2}\text{sign}(s) - \beta \int \text{sign}(s)$$

Observer gains can be adaptive [2]

→ The auxiliary sliding variable is stabilized in finite-time

→ The nominal dynamics are recovered in spite of disturbances and model

uncertainties  $\sigma^{(r)} = \nu_n$

# Incremental Sliding Mode Control

- ❖ Stabilization of the nominal dynamics

$$\boldsymbol{\sigma}^{(r)} = \boldsymbol{\nu}_n$$

- ❖ Asymptotic stabilization

$$\boldsymbol{\nu}_n = -\mathbf{K}_{r-1}\boldsymbol{\sigma}^{(r-1)} - \mathbf{K}_{r-2}\boldsymbol{\sigma}^{(r-2)} \dots - \mathbf{K}_0\boldsymbol{\sigma}$$

- ❖ Finite-time stabilization

$$\begin{aligned}\boldsymbol{\nu}_n &= [\nu_{n,1}, \nu_{n,2}, \dots, \nu_{n,m}]^T \\ \nu_{n,i} &= -K_{r-1,i}|\sigma_i^{(r_i-1)}|^{\alpha_{r_i,i}}\text{sign}(\sigma_i^{(r_i-1)}) - \dots \\ &\quad -K_{0,i}|\sigma_i|^{\alpha_{1,i}}\text{sign}(\sigma_i), \quad i = 1, \dots, m\end{aligned}$$

# SIMULATION



# Dynamic Model

- ❖ Dynamic equation

$$m_s \ddot{q} + c_s(q) \dot{q} + k_s(q) q = d_s + F_u \quad \text{Generalized coordinate}$$

$$m_s = 0.5, \quad c_s(q) = 0.05 \cdot f(q), \quad k_s(q) = 554.4744 \cdot f(q)$$

$$f(q) = 0.5 \cdot (q/0.05)^2 + 1 \quad \text{Nonlinear stiffness and damping}$$

- ❖ External disturbances

$$d_s = 7.5 \sin(5t) \quad \text{Transport delay of 3 seconds}$$

- ❖ Initial conditions

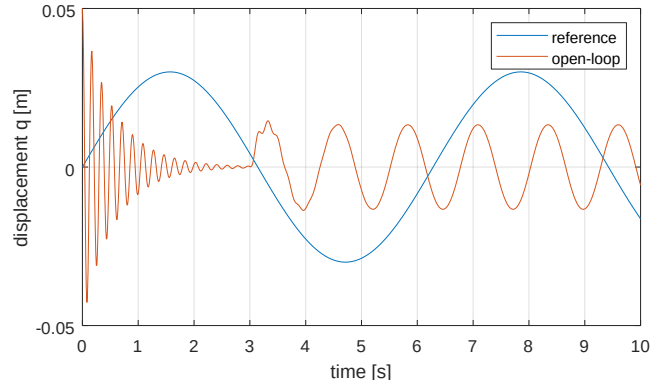
$$\dot{q}(t = 0) = 0, \quad q(t = 0) = 0.05$$

- ❖ Tracking reference

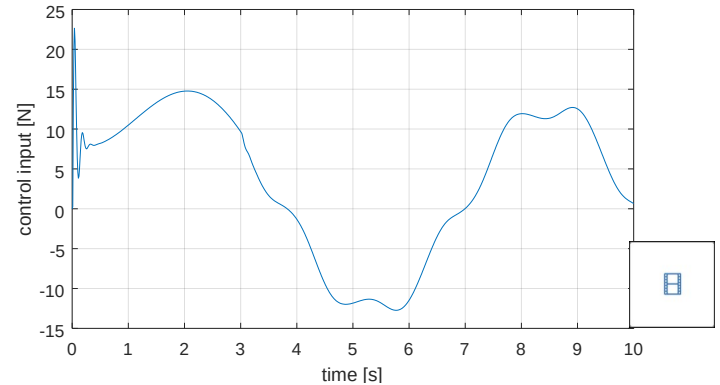
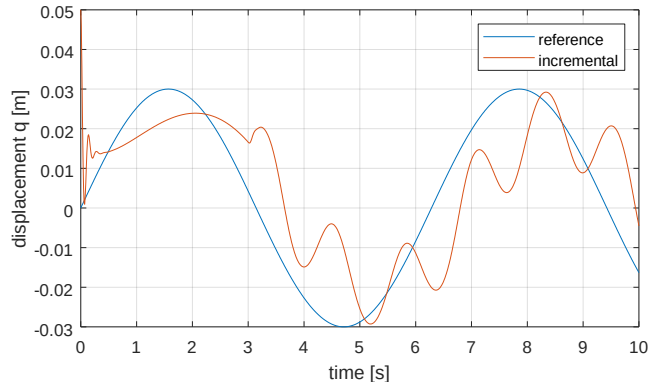
$$q_{\text{ref}} = 0.03 \sin(t)$$

# Simulation Results

## ❖ Open-loop responses

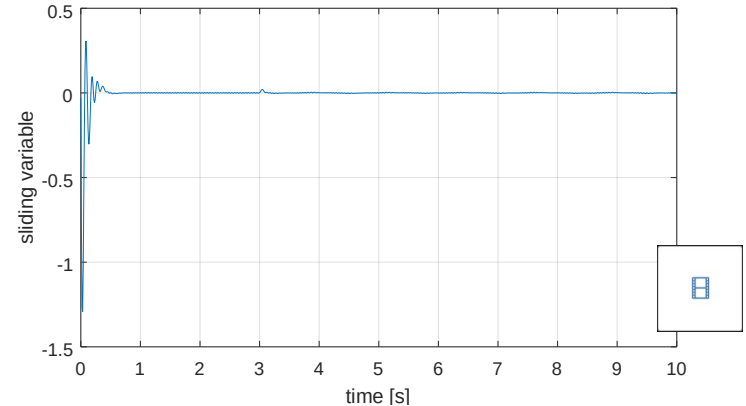
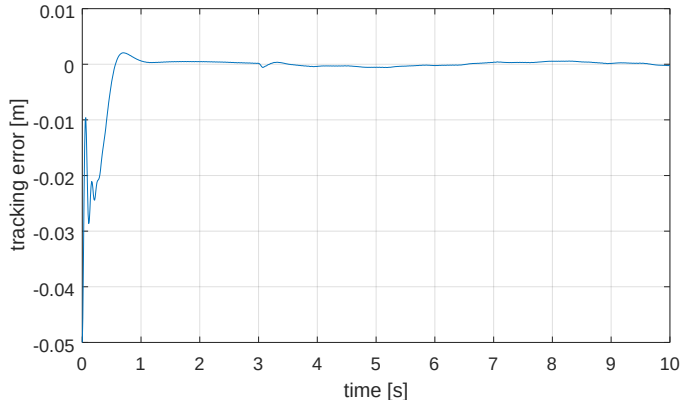
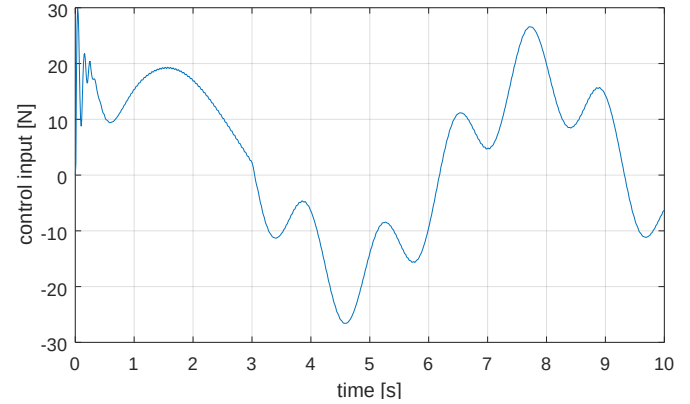
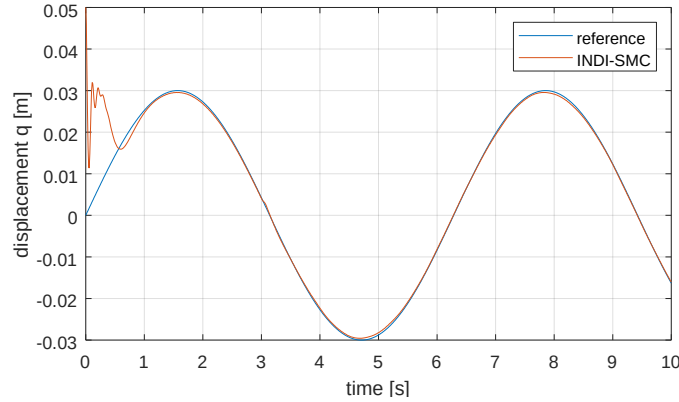


## ❖ Incremental control



# Simulation Results

## ❖ Incremental control + sliding mode disturbance observer



first-order actuator  
dynamics with time  
constant of 0.04

# CONCLUSIONS



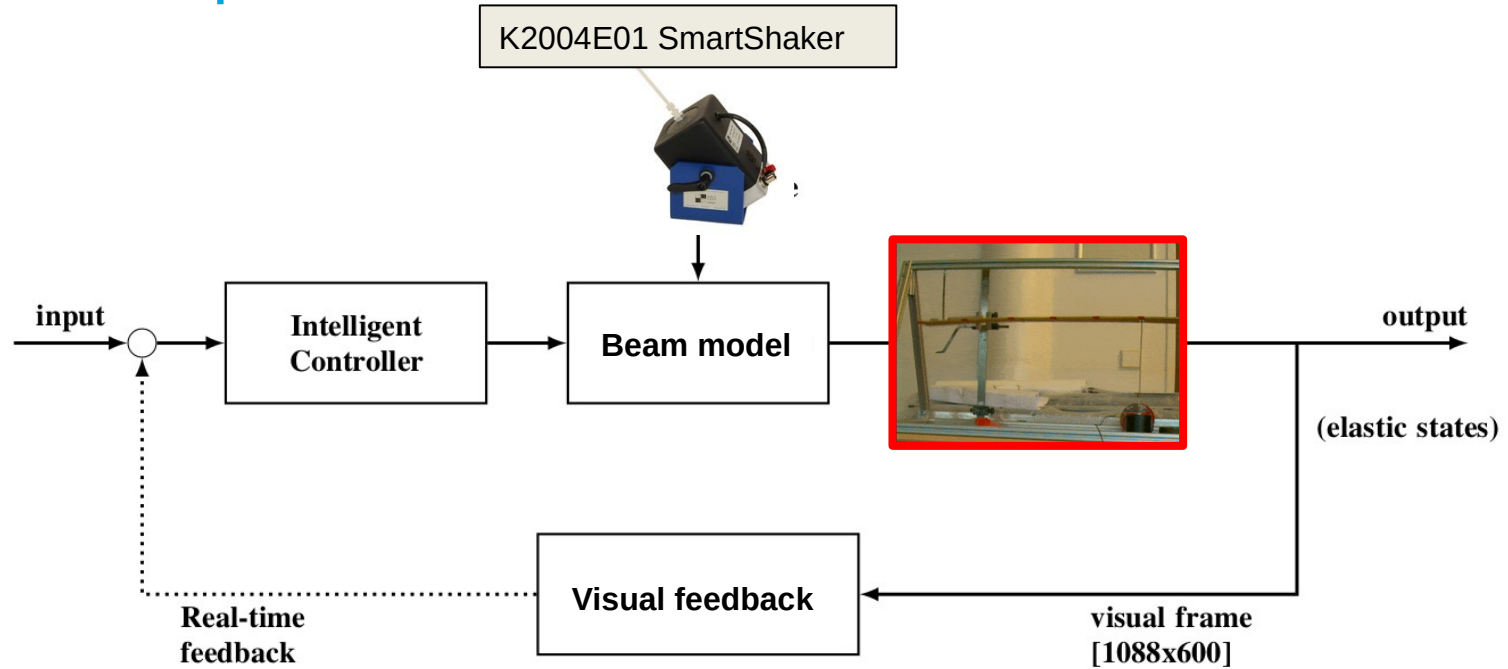
# Conclusions

- Visual tracking is suitable as adaptive model free sensor
- Incremental sliding mode tracks well but performance can be improved
- Sliding mode disturbance observer significantly improved performance
- Morning control and non-linear dynamics can benefit from robust model-free sensing and control methods

# FUTURE WORK

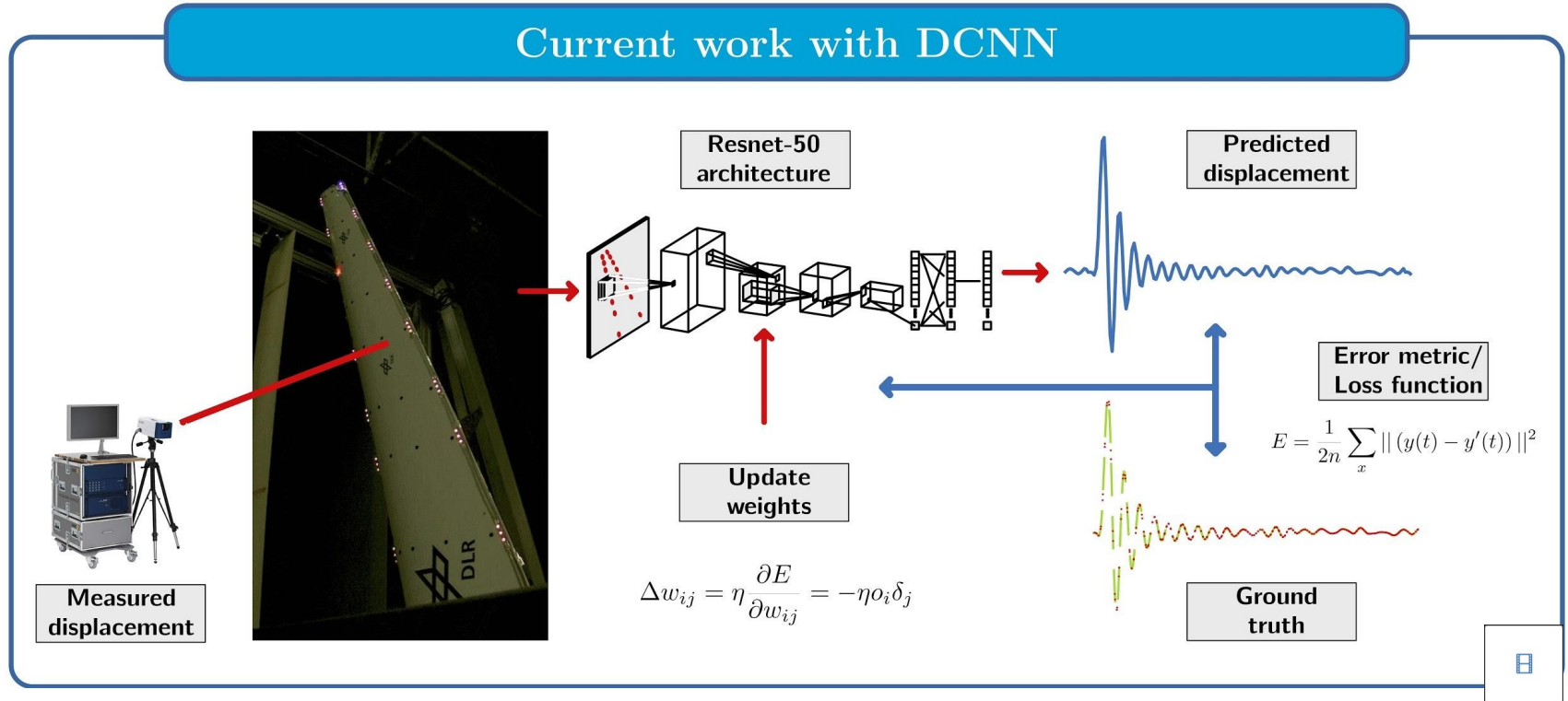


# Closed loop visual feedback control

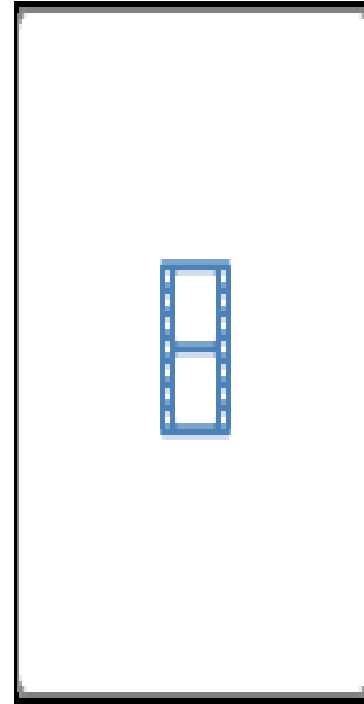
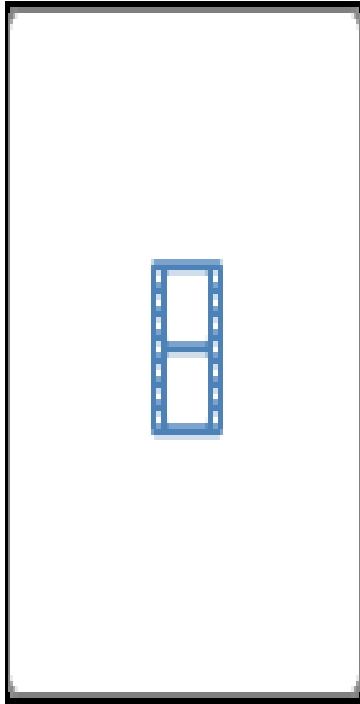


# Deep learning methods

## Current work with DCNN



# Smart-X adaptive morphing control



THANK YOU

