Learning Stable Dynamical Systems for Visual Servoing

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Visual Servoing (VS) at a glance

► The camera is moved to a desired pose using *visual feedback*

► In normal conditions, VS realizes *simple* trajectories

► More complex motion can be achieved adding *tasks* or *constraints*
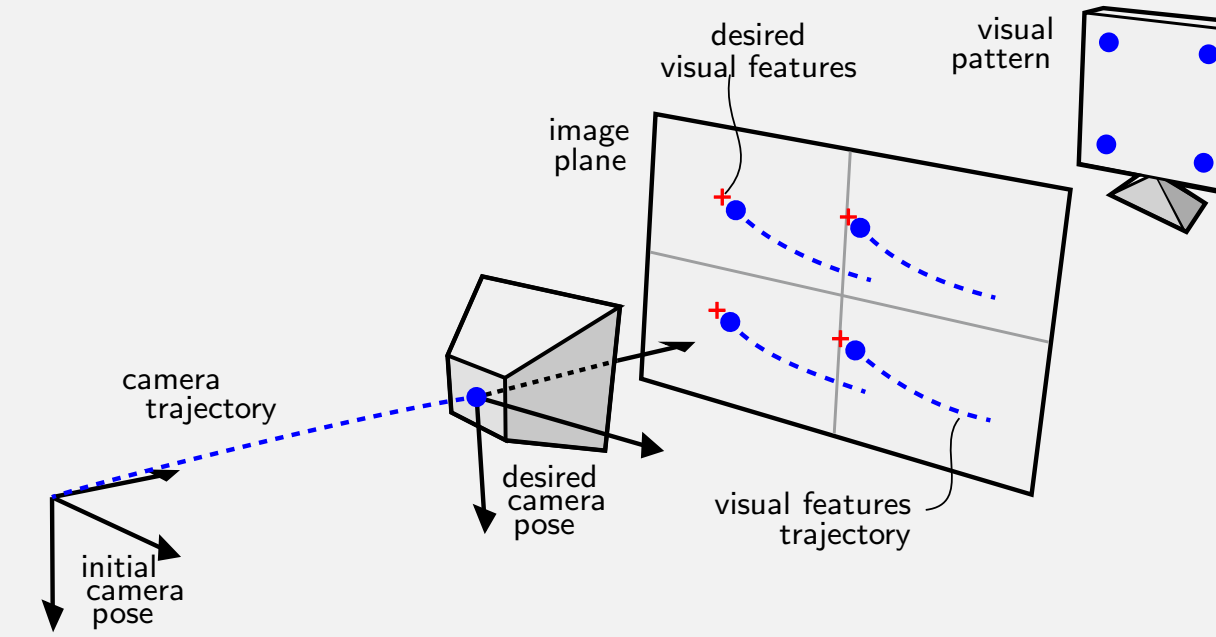
Dynamical Systems (DS) at a glance

► Complex motion is learned by imitating previous *demonstrations*

► DS realize imitation learning keeping the original controller *stability*

► DS are strictly dependent on *proprioception*
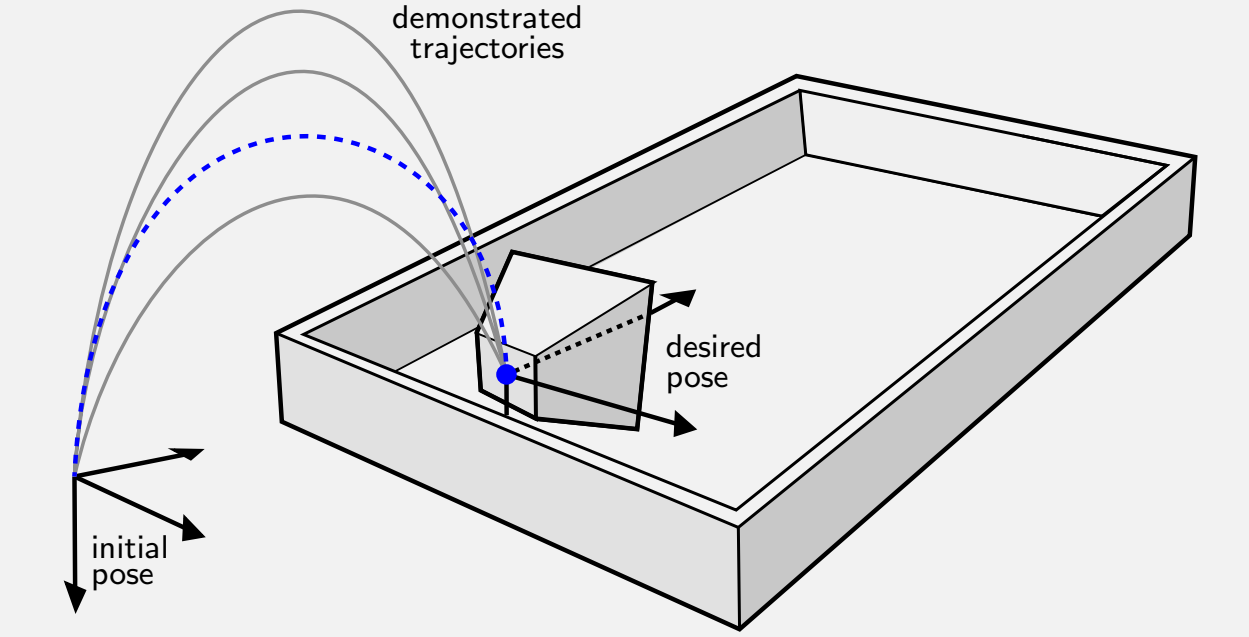
Motivation

► Realize *easy-to-use* and *adaptive* robot controllers
  ► *No explicit coding* of additional skills
  ► Integrate *exteroception* to adapt to environment changes

Proposed Solution: Combine DS and VS

► DS enable *additional skills* without explicitly coding them into VS

► VS integrates *exteroception* to adapt DS to environment changes

► The combination benefit is shown by applying *3 existing DS methods to VS*
  ► *Reshaped Dynamical System* (RDS) [1]
  ► *Control Lyapunov Function-based Dynamic Movements* (CLF-DM) [2]
  ► *Fast Diffeomorphic Matching* (FDM) [3]

[1] M. Saveriano and D. Lee, "Incremental skill learning of stable dynamical systems," in *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2018, pp. 6574–6581.

[2] S. M. Khansari-Zadeh and A. Billard, "Learning control Lyapunov function to ensure stability of dynamical system-based robot reaching motions," *Robotics and Autonomous System*, vol. 62, no. 6, pp. 752–765, 2014.

[3] N. Perrin and P. Schlehuber-Caissier, "Fast diffeomorphic matching to learn globally asymptotically stable nonlinear dynamical systems," *Systems & Control Letters*, vol. 96, pp. 51–59, 2016.
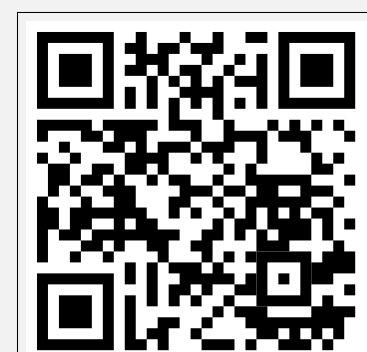
Dataset and Simulation Analysis

LASA dataset [4] extended with visual features trajectories
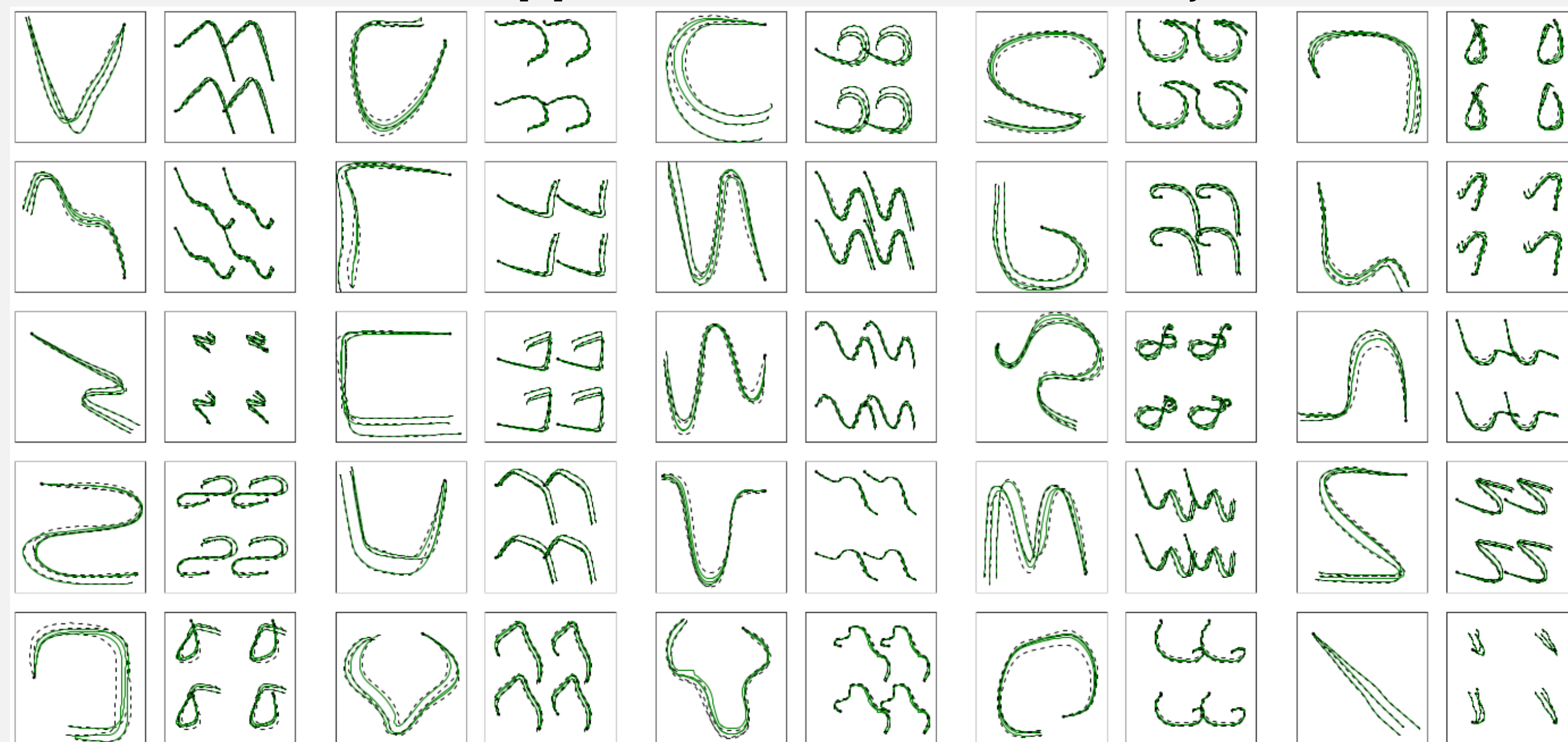
[4] S. M. Khansari-Zadeh and A. Billard, "Learning stable non-linear dynamical systems with Gaussian mixture models," *IEEE Trans. Robot.*, vol. 27, no. 5, pp. 943–957, 2011.
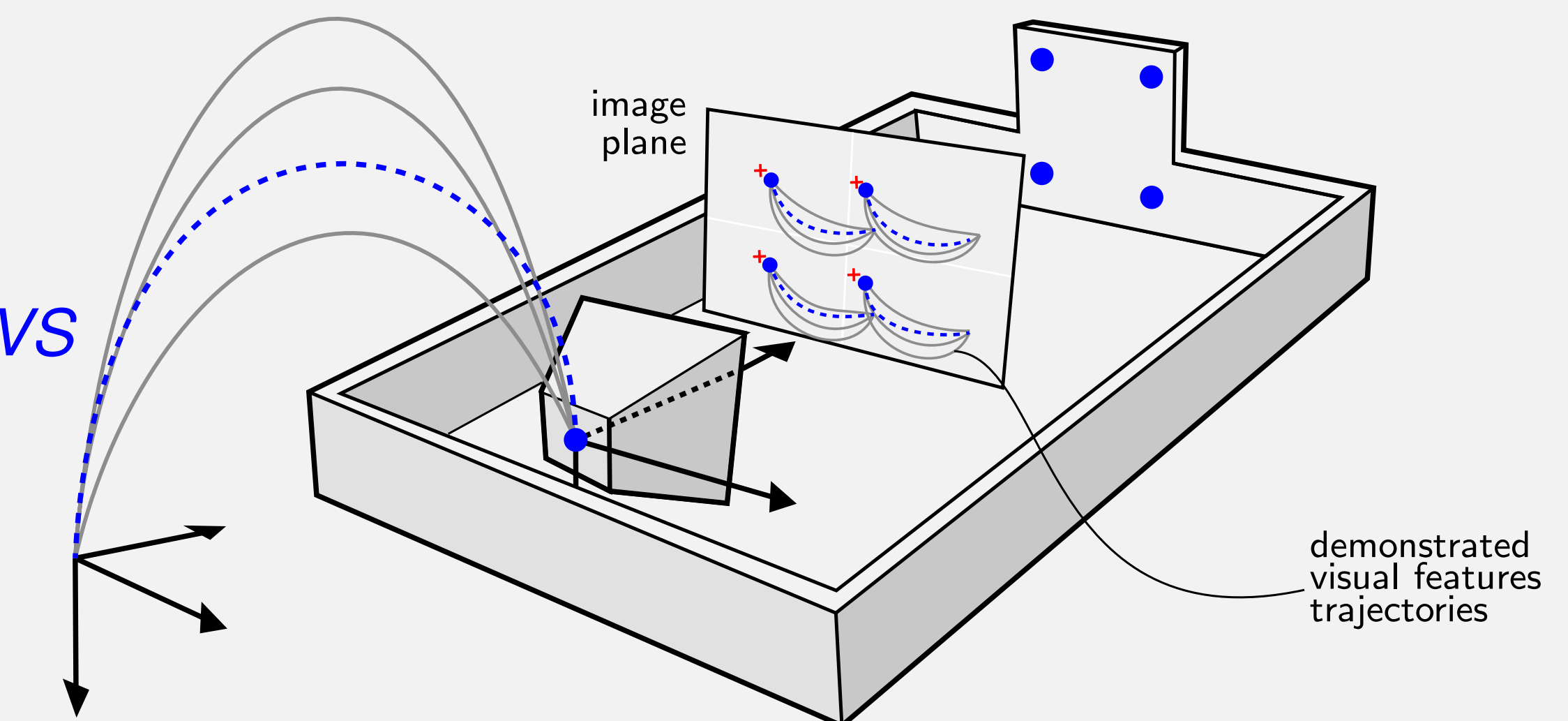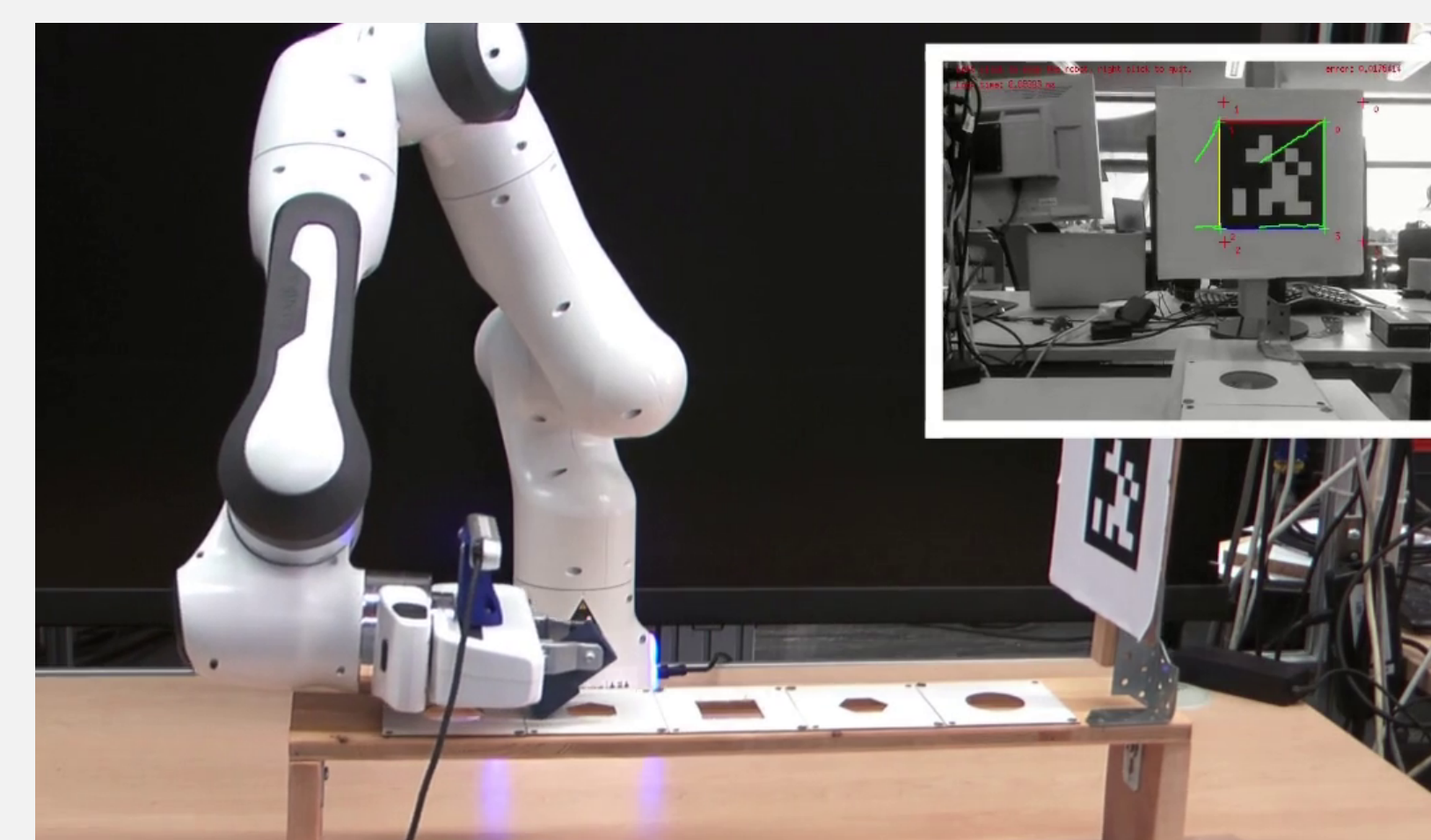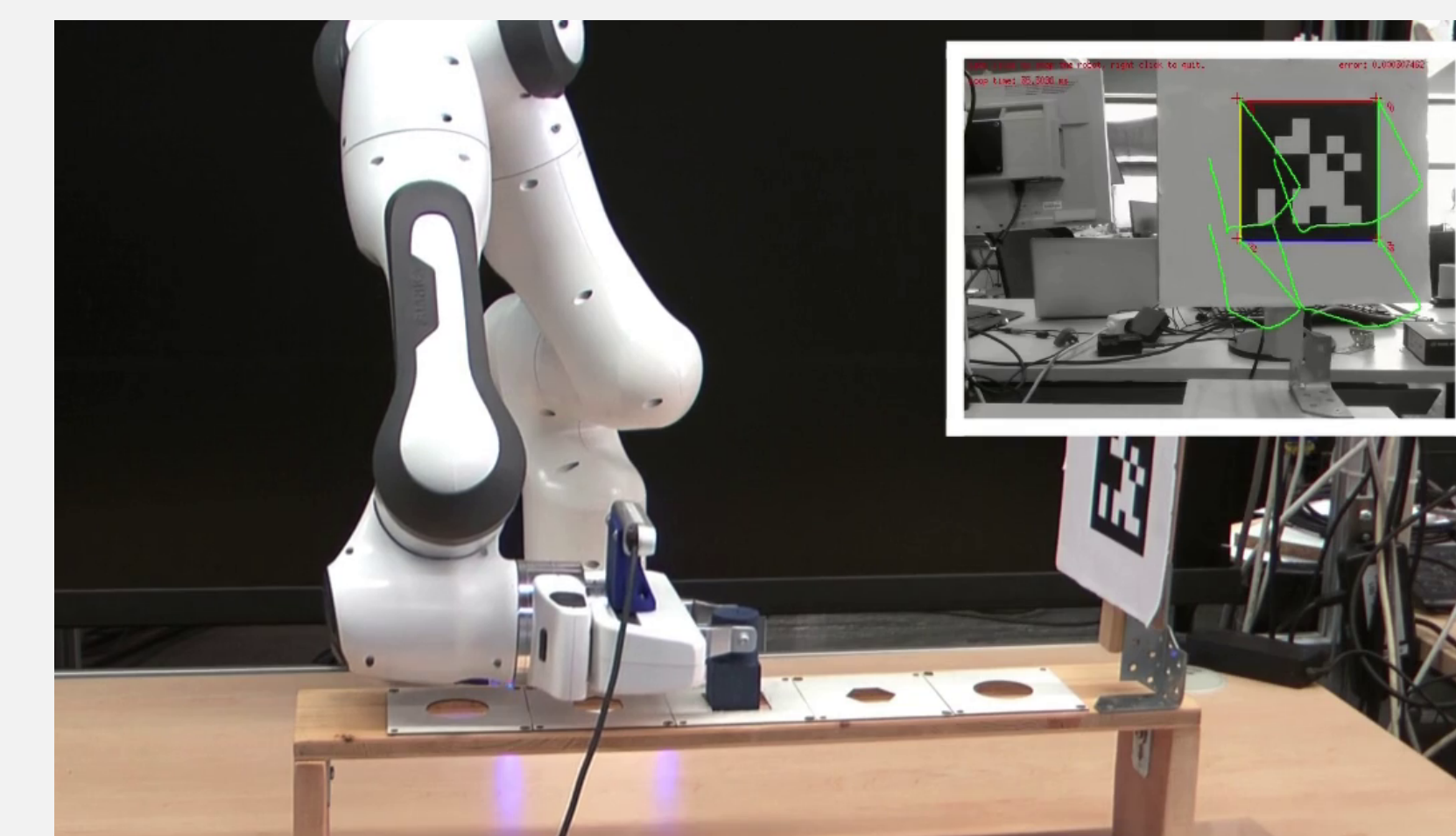
RDS | CLF-DM | FDM
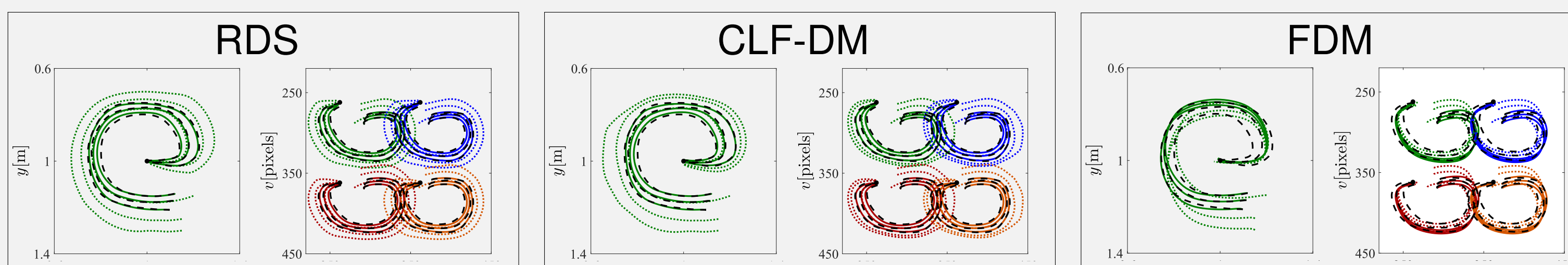
METHOD	HYPER.	POS. ERR. [mm]	VEL. ERR. [mm/s]	FEAT. ERR. [pixels]	TRAIN. TIME [ms]
RDS	7	25 ± 39	105 ± 72	9 ± 15	546 ± 1431
RDS	11	17 ± 13	86 ± 42	6 ± 5	697 ± 1540
CLF-DM	$7 + 2$	36 ± 55	121 ± 102	14 ± 21	9298 ± 4026
CLF-DM	$11 + 2$	19 ± 14	82 ± 52	7 ± 5	9291 ± 3886
FDM	150	60 ± 11	118 ± 45	14 ± 6	173 ± 376
FDM	50	59 ± 11	120 ± 45	14 ± 6	53 ± 105

Dataset and code of two DS methods in a simulated VS are available at
`https://github.com/matteosaveriano/ilvs`
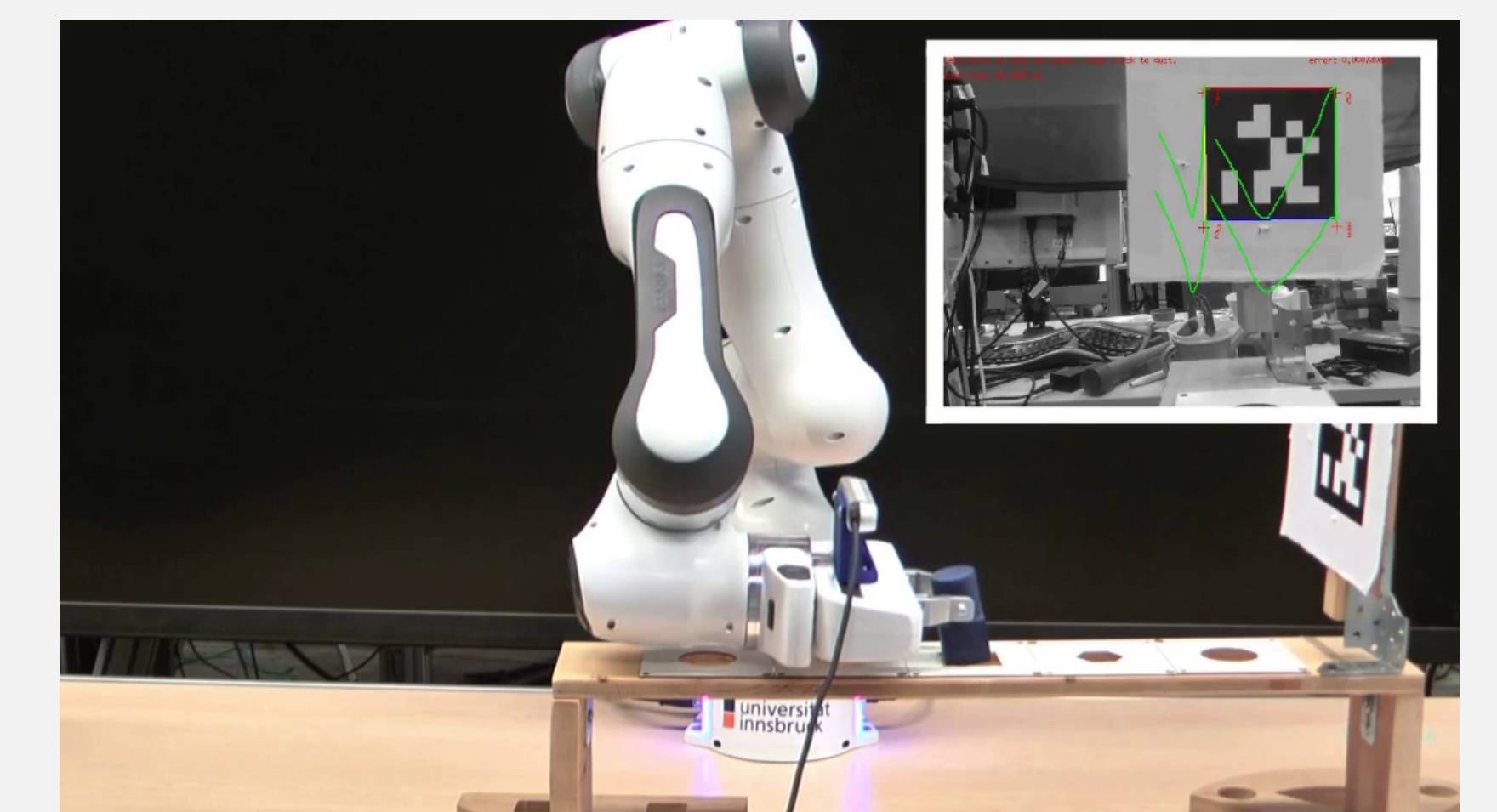← Scan the QR code!

Peg-in-Hole Experiments

standard VS fails at avoiding collision   DS-based VS successfully realizes the task, also with a shifted target

video available at `https://youtu.be/aRO93O_fpC8` (IDSIA's YouTube Channel)

Future Work

► Coding duties can be even more reduced removing the explicit image processing

► Our approach can ease the visual controller deployment in complex platforms like humanoids

► Integration with interaction strategies can ease both data collection and more advanced tasks