Robot Learning Using Physics-Informed Models

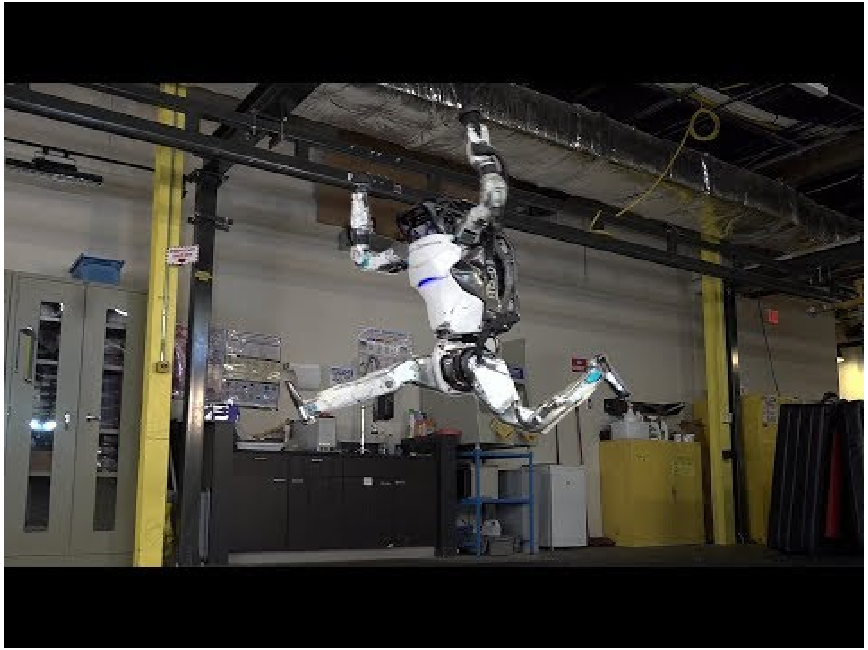
(Utilise Computer Graphics for more efficient Machine Learning in Robotics)

Martin Asenov

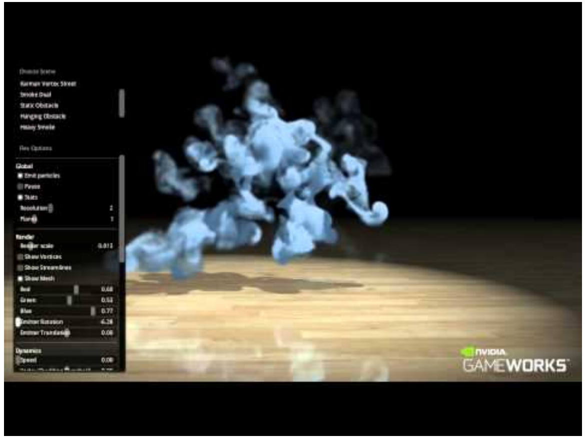
Supervisors:
Dr. Subramanian Ramamoorthy and Dr. Kartic Subr

ImageNet moment in Robotics?

Recent impressive advancements



Still something missing?



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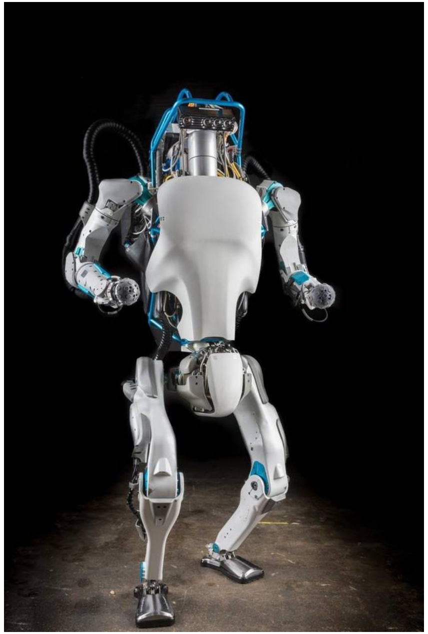

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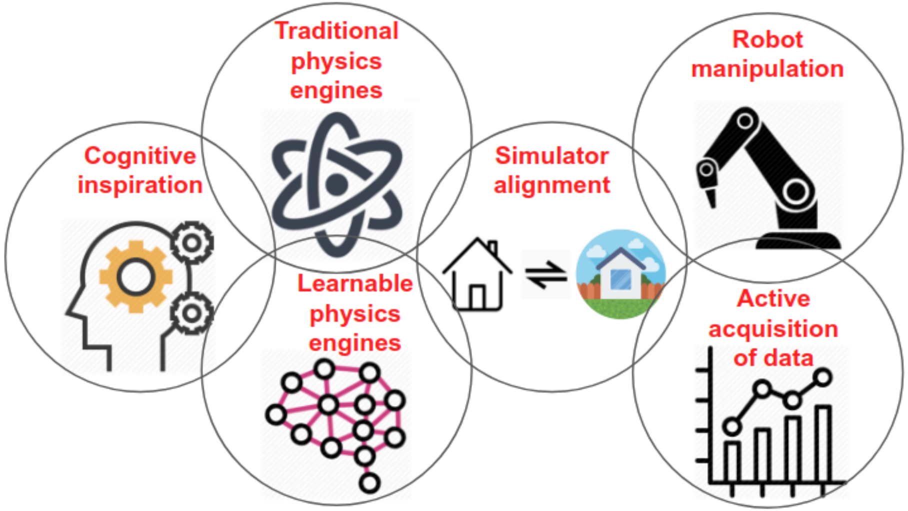
Related work - overview



Related work - overview

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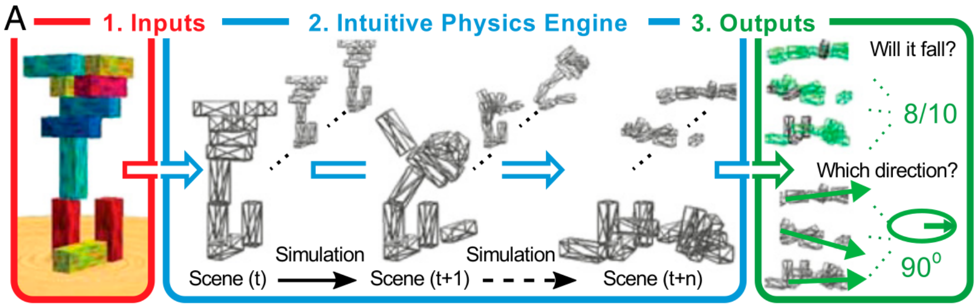

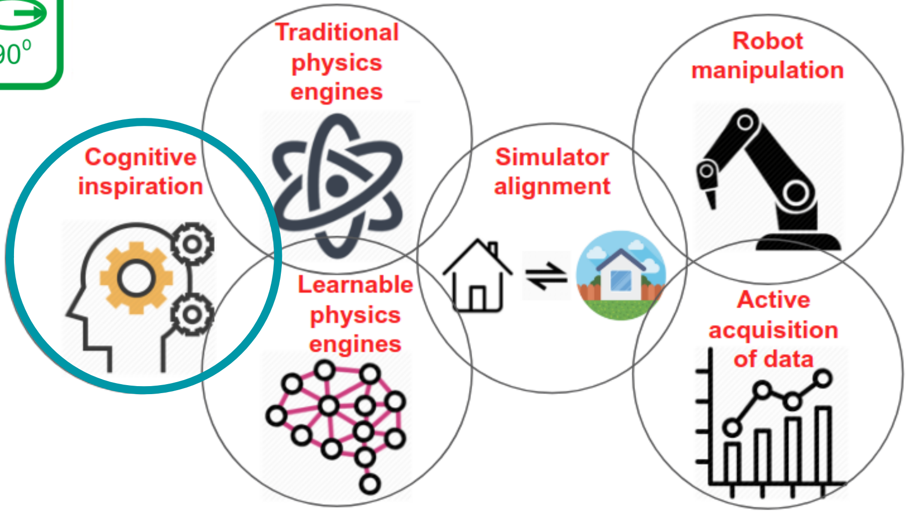

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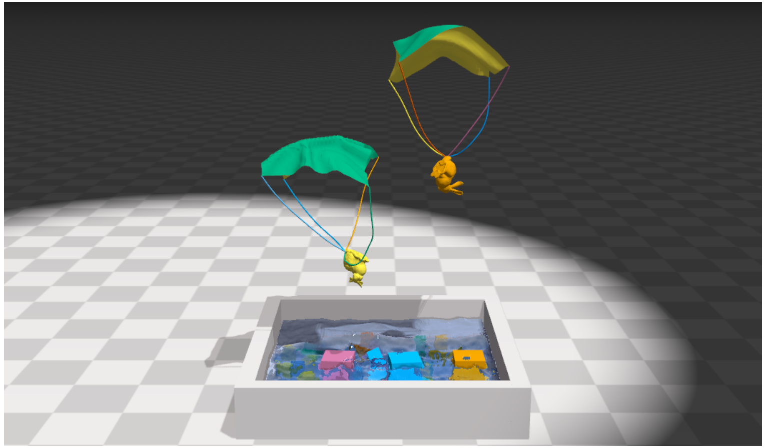

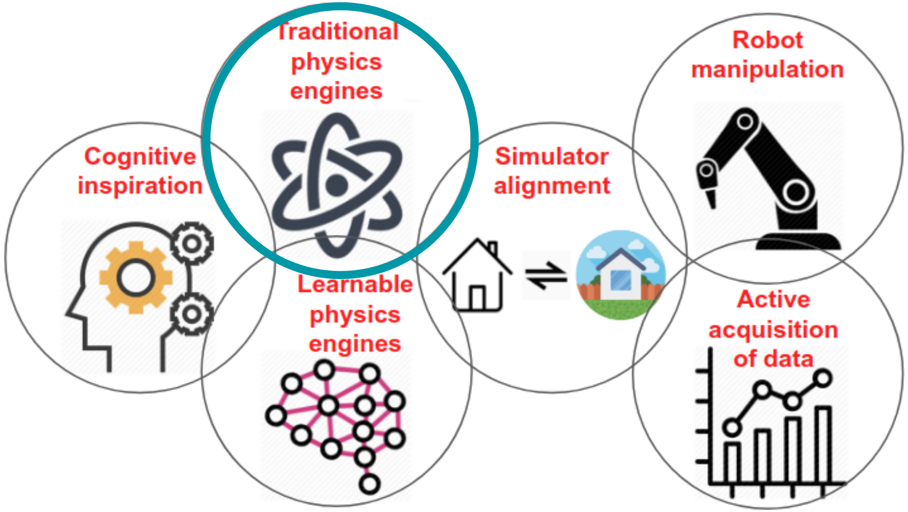

Related work - overview

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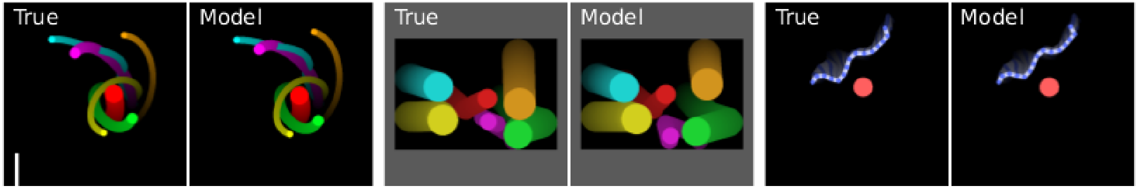

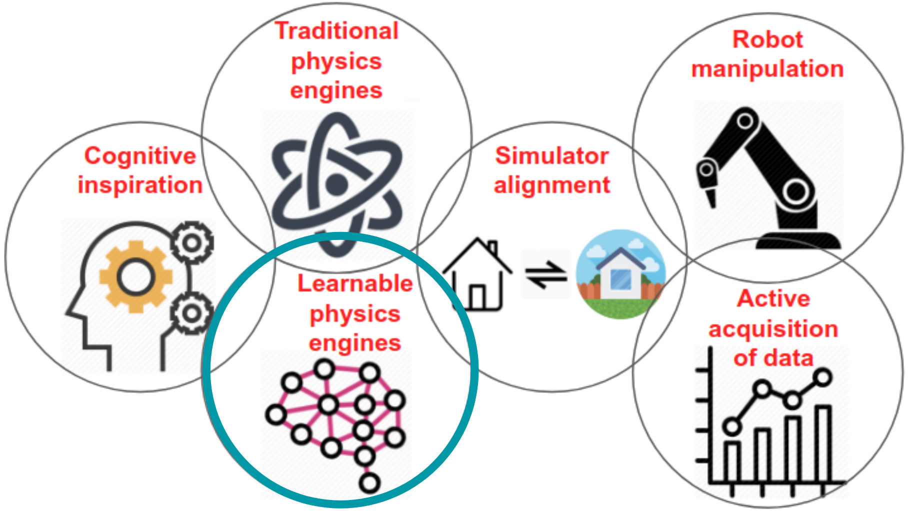

Related work - overview

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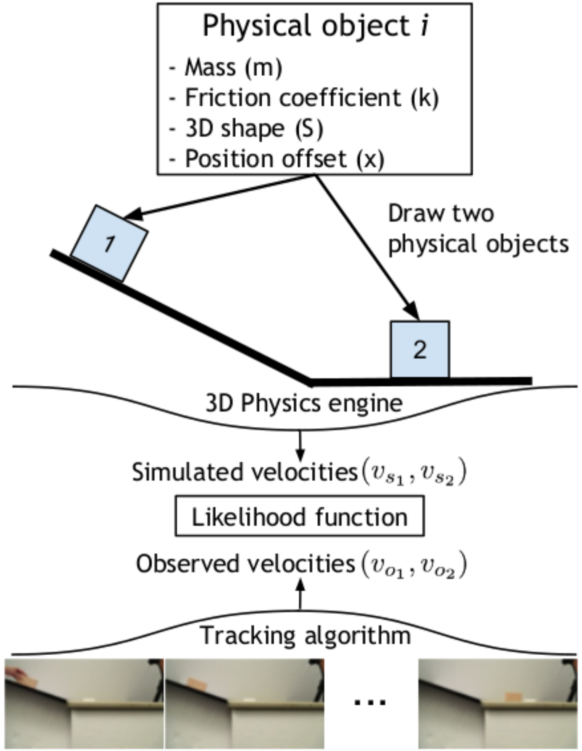

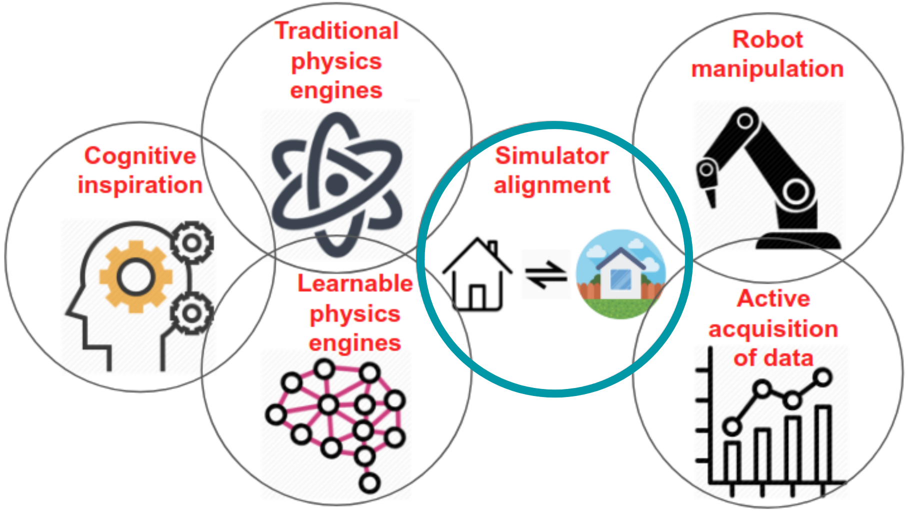

Related work - overview

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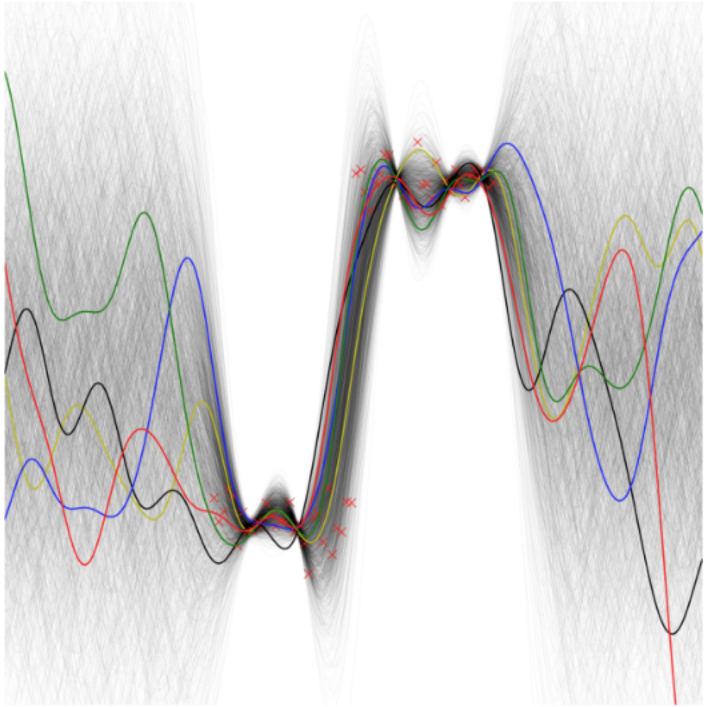

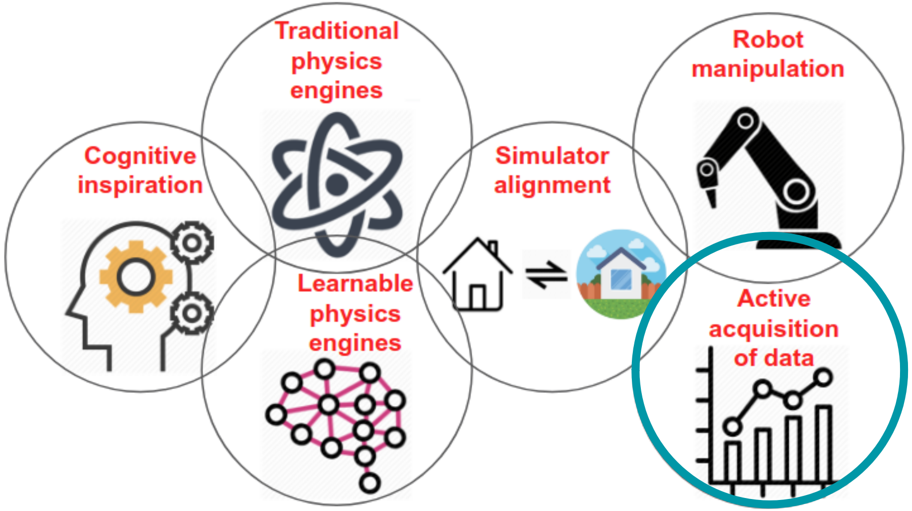

Related work - overview

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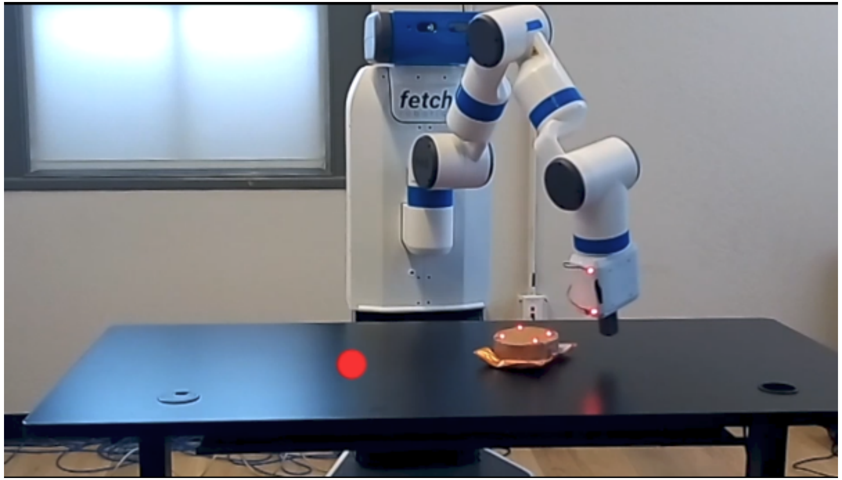

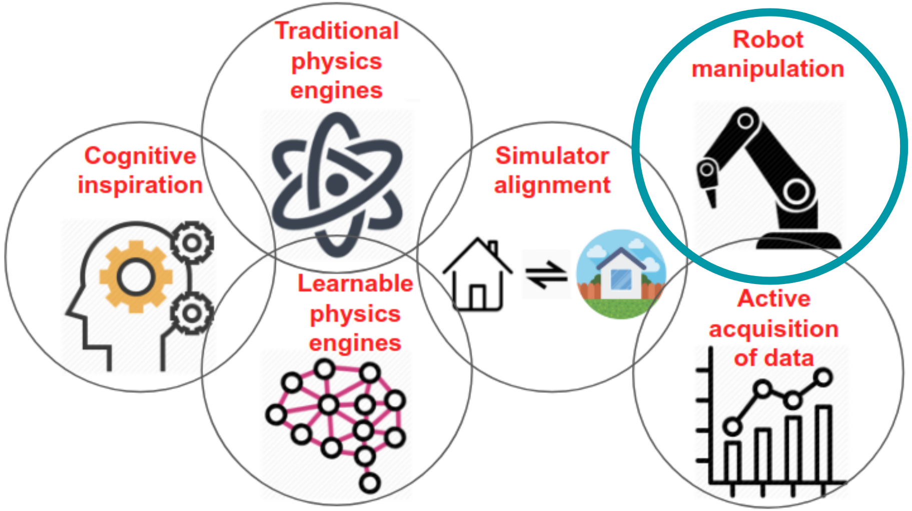

My work - using simulations as models in robotics

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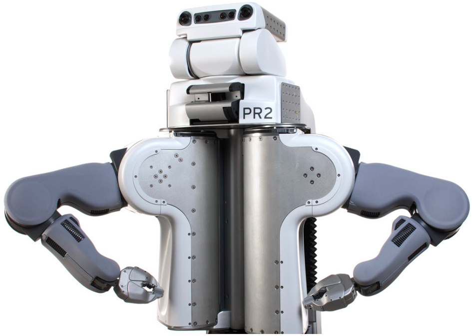

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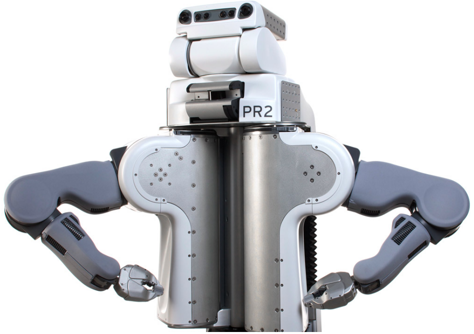

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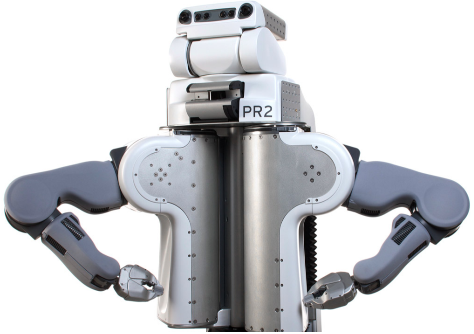

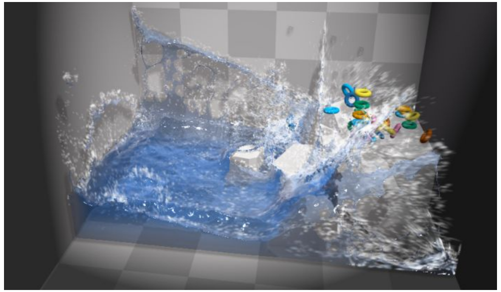

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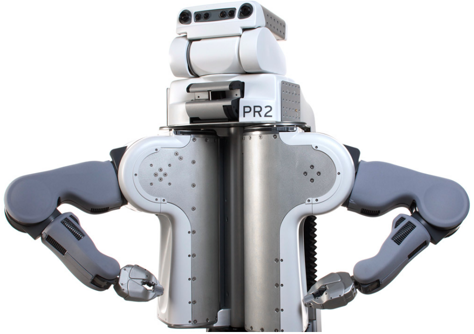

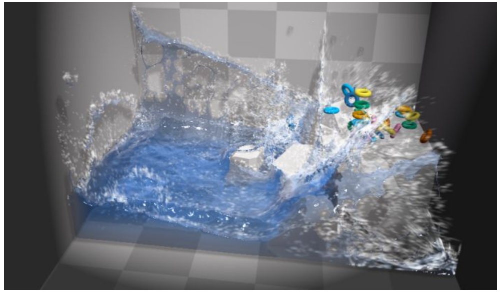

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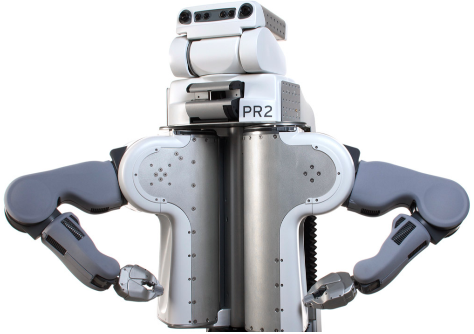

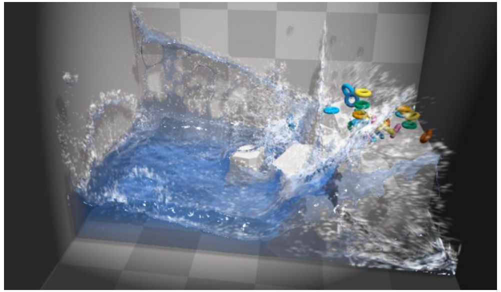

My work - using simulations as models in robotics

Active Localization of Gas Leaks Using Fluid Simulation

Martin Asenov, Marius Rutkauskas, Derryck Reid, Kartic Subr, and Subramanian Ramamoorthy

EDINBURGH CENTRE FOR ROBOTICS
Innovation Ready

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Motivation

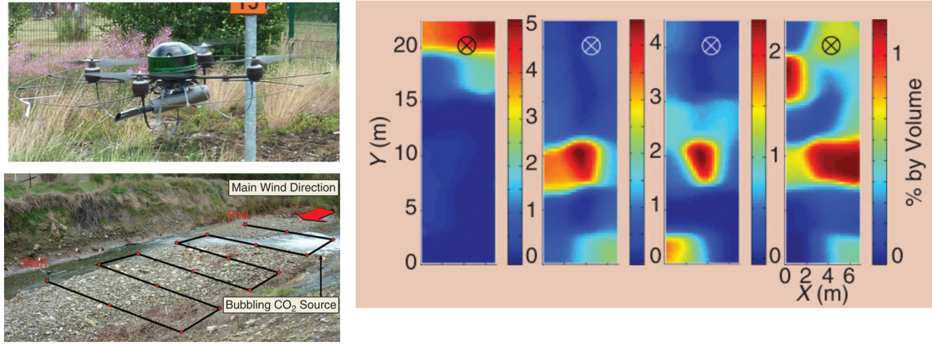
Detection and **localization** of gas leakages

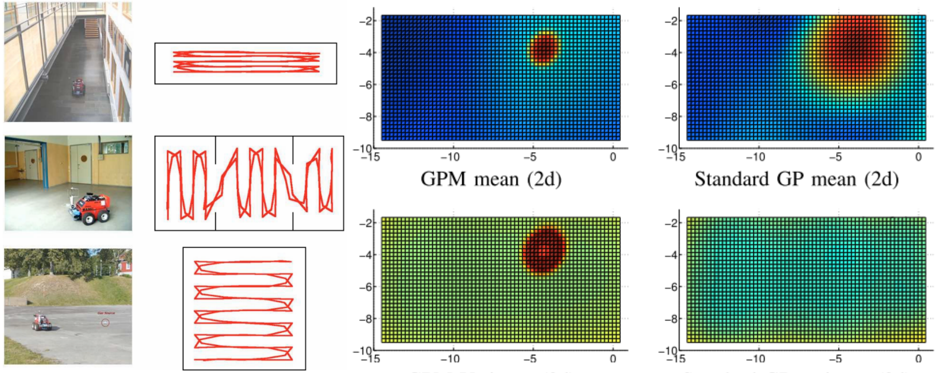
It’s often dangerous and hard to people in...

while it’s crucial the leakage is found quickly.

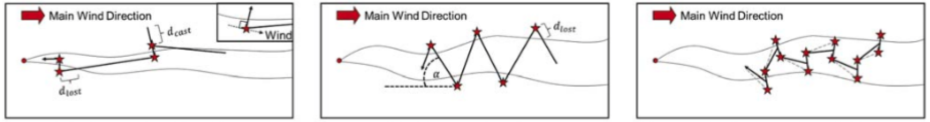
Related work

Regression Approaches

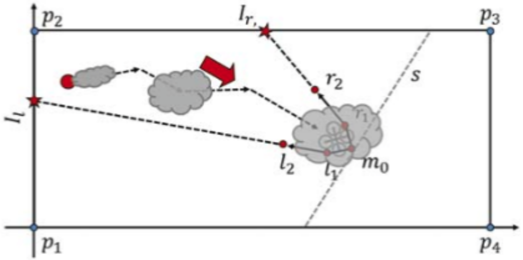


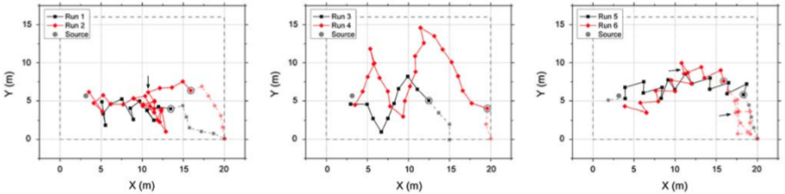


Gradient following



(a) Surge-Cast Algorithm (b) Zigzag Algorithm (c) Pseudo Gradient-based Algorithm





(a) Surge-Cast (b) Zigzag (c) Gradient-based

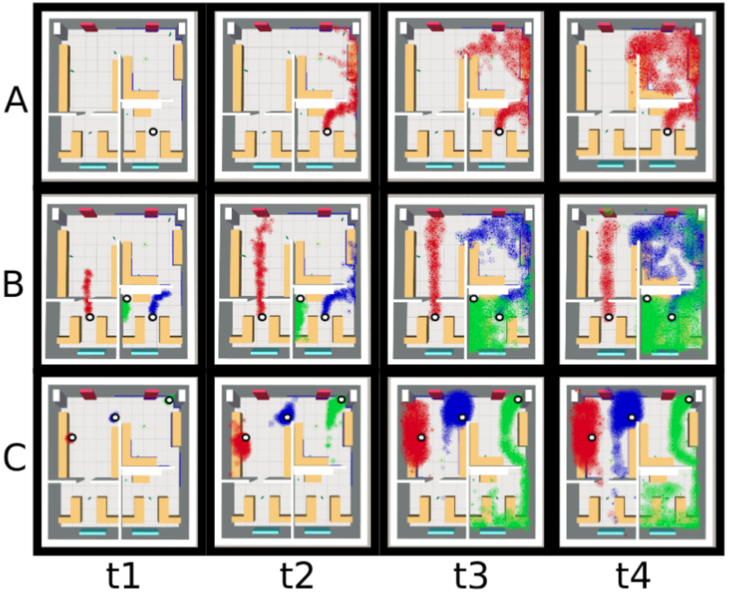
[1] Neumann, Patrick P., et al. "Autonomous gas-sensitive microdrone: Wind vector estimation and gas distribution mapping." *IEEE robotics & automation magazine* 19.1 (2012): 50-61.

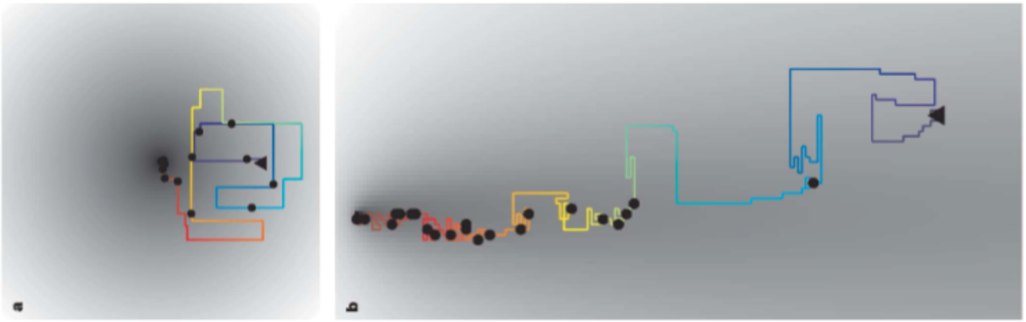
[2] Stachniss, Cyril, et al. "Gas distribution modeling using sparse Gaussian process mixture models." Robotics: science and systems conference 2008, Zürich, Switzerland, June 25-28. MIT press, 2008.

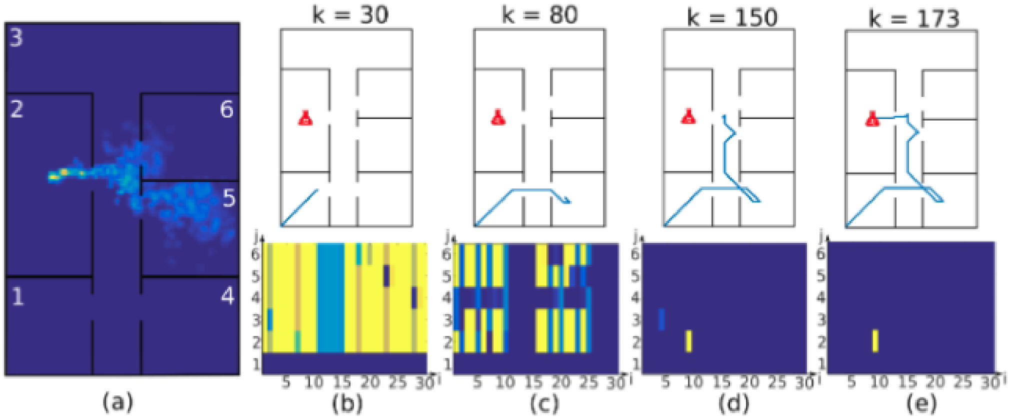
[3] Neumann, Patrick P., et al. "Gas source localization with a micro-drone using bio-inspired and particle filter-based algorithms." Advanced Robotics 27.9 (2013): 725-738.

Related work

Using simulations as models





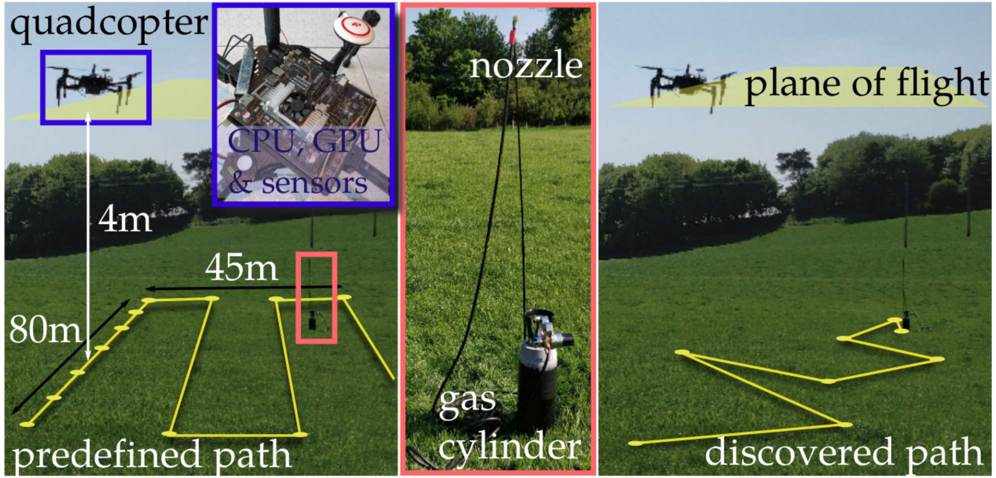


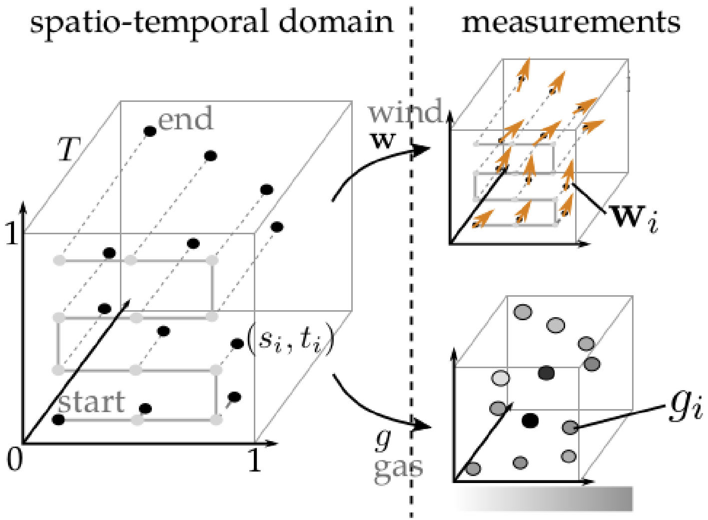
[1] Vergassola, Massimo, Emmanuel Villermaux, and Boris I. Shraiman. "'Infotaxis' as a strategy for searching without gradients." Nature 445.7126 (2007): 406.
[2] Sanchez-Garrido, Carlos, Javier Monroy, and Antonio Javier Gonzalez-Jimenez. "Probabilistic localization of gas emission areas with a mobile robot in indoor environments." (2018).
[3] Monroy, Javier, et al. "GADEN: A 3D gas dispersion simulator for mobile robot olfaction in realistic environments." Sensors 17.7 (2017): 1479.

Problem formulation

Motivating problem: localize a gas leakage in an open field using a UAV to collect gas concentration readings and estimate the wind

Challenges: very limited data, while accounting for wind dynamics, gas dispersion, etc.

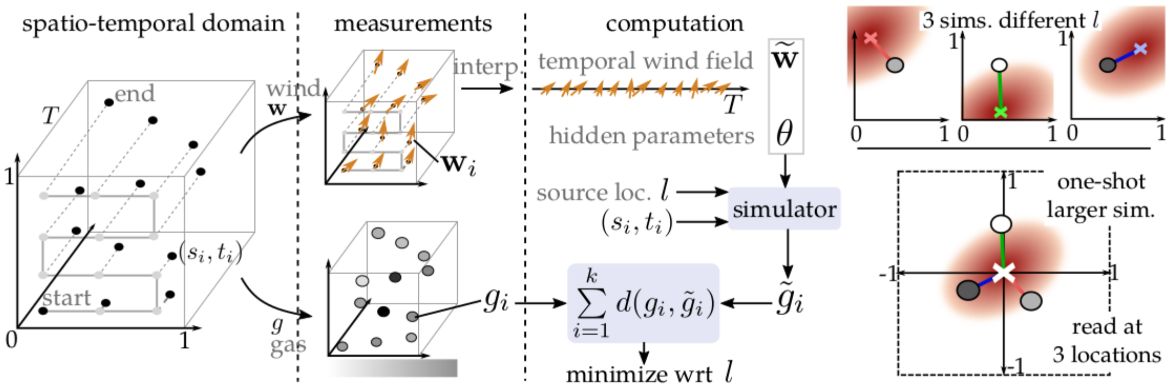




Approach: Use fluid simulation as a model and align to the observed data in order to capture those dynamics

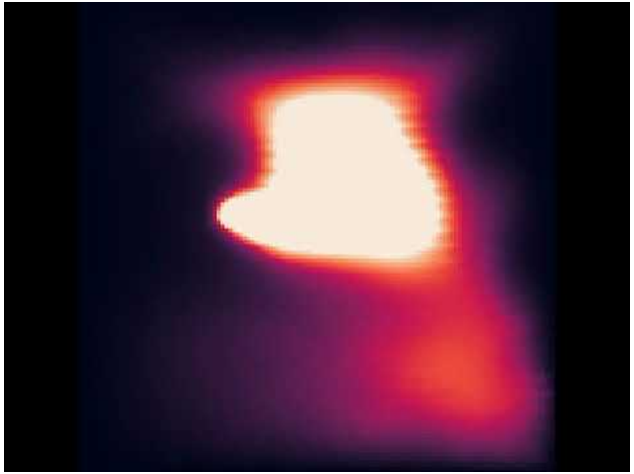
M. Asenov, M. Rutkauskas, D.T. Reid, K. Subr, S. Ramamoorthy, **Active localization of gas leaks using fluid simulation**, *IEEE Robotics and Automation Letters*, Vol 4(2), 2019.

Proposed approach



(a) Summary of notation

(b) Key idea



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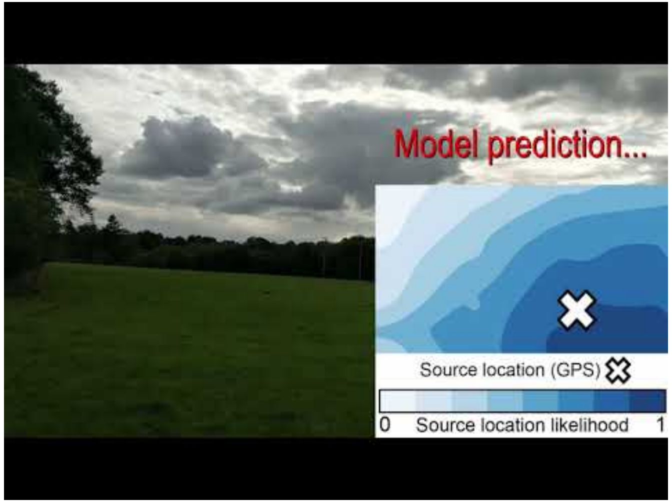
Experimental setup

Offline experiments
(UAV)



Online experiments
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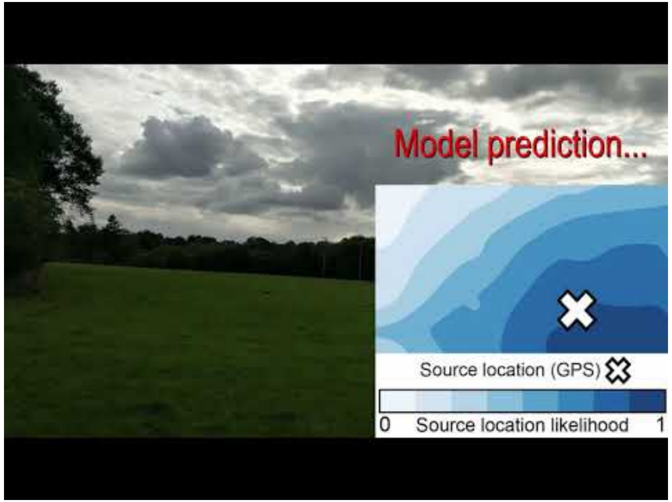
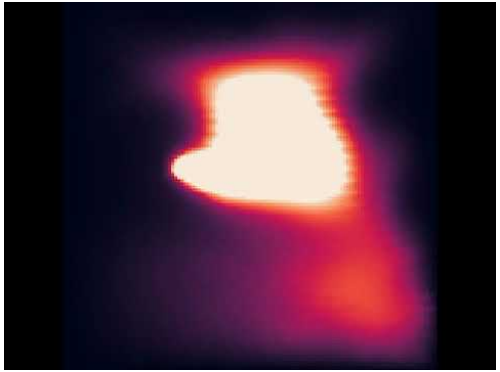
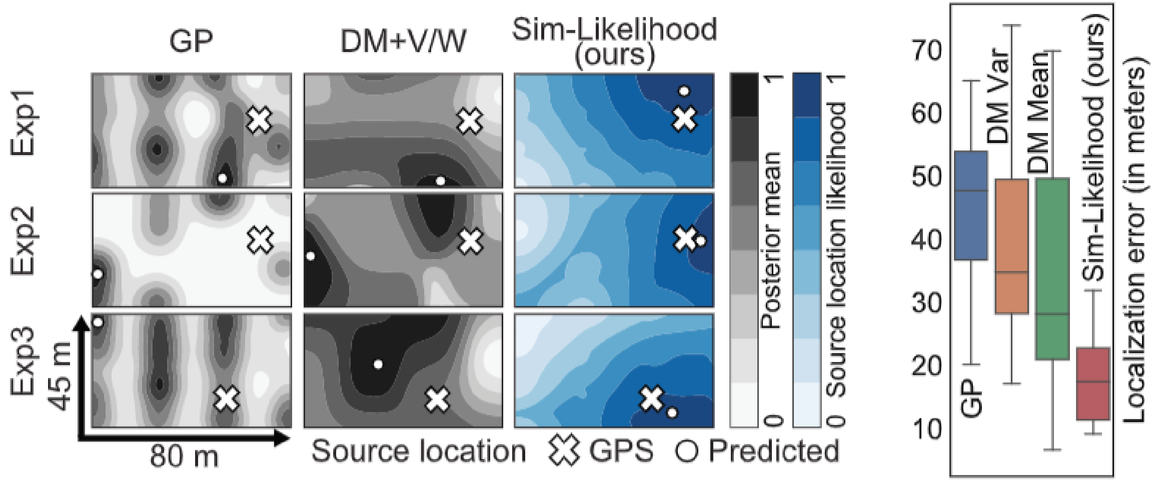


Online experiments
(Noisy simulator)



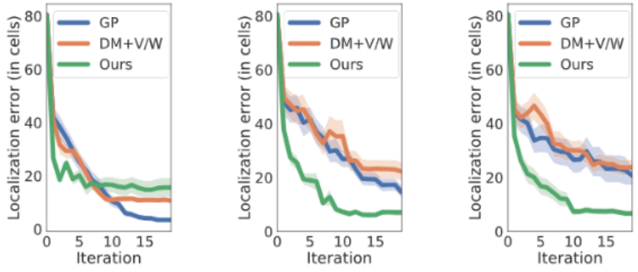
Results - regression baselines

Offline experiments (with a UAV)



(a) Predictions (b) Error

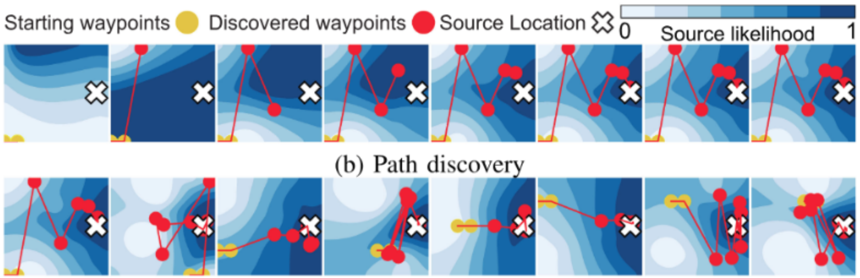
Online experiments (Noisy simulator)



(a) No wind (b) Constant wind (c) Variable wind

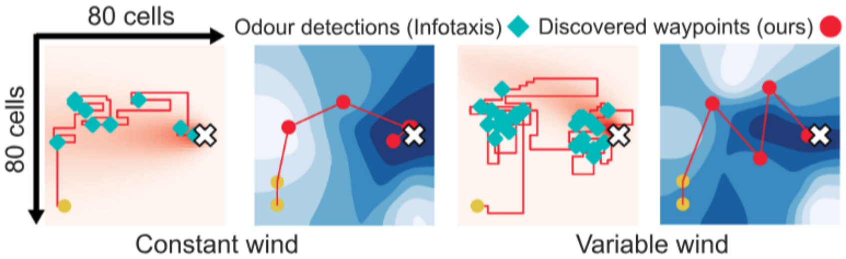
Results - active sensing

Online experiments (Noisy simulator)

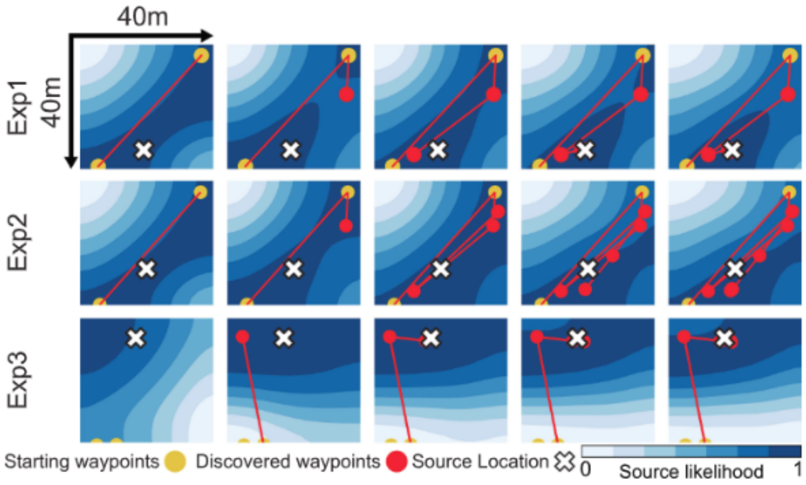


(b) Path discovery

(c) Different initialization

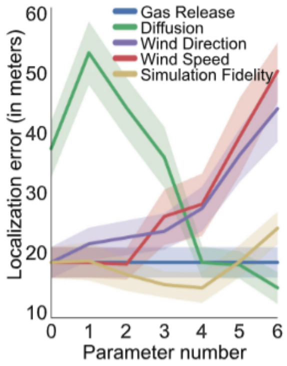


Online experiments (UAV)

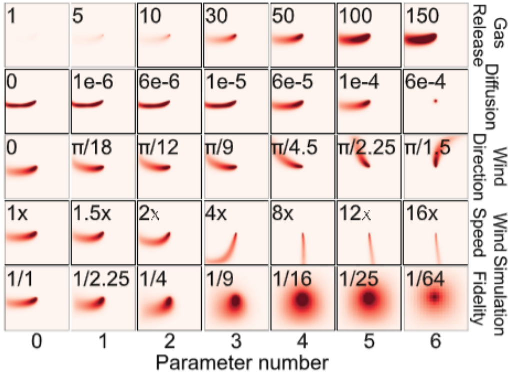


Results - sensitivity analysis, speed and accuracy

Offline experiments
(UAV)

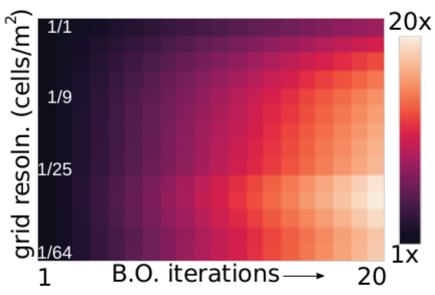


(a) Sensitivity to hyperparameters

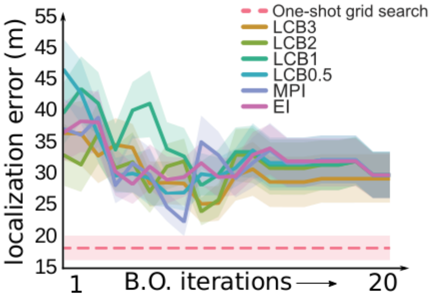


(b) Effect of the hyperparameters

Offline experiments
(UAV)

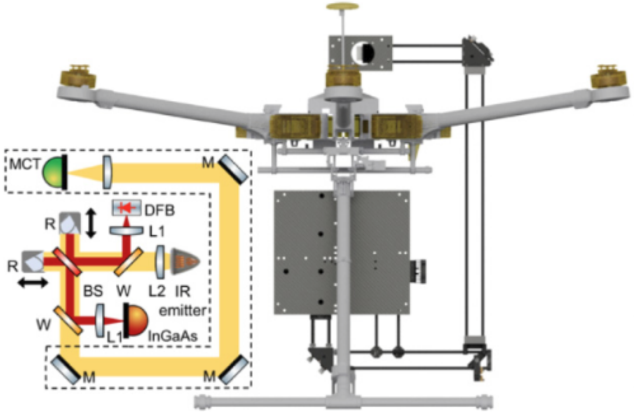


(a) speedup OGS: BO



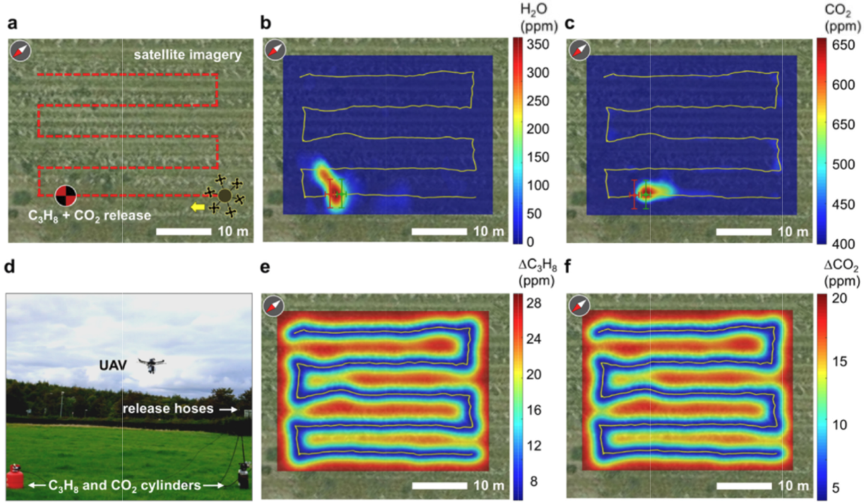
(b) Localization error

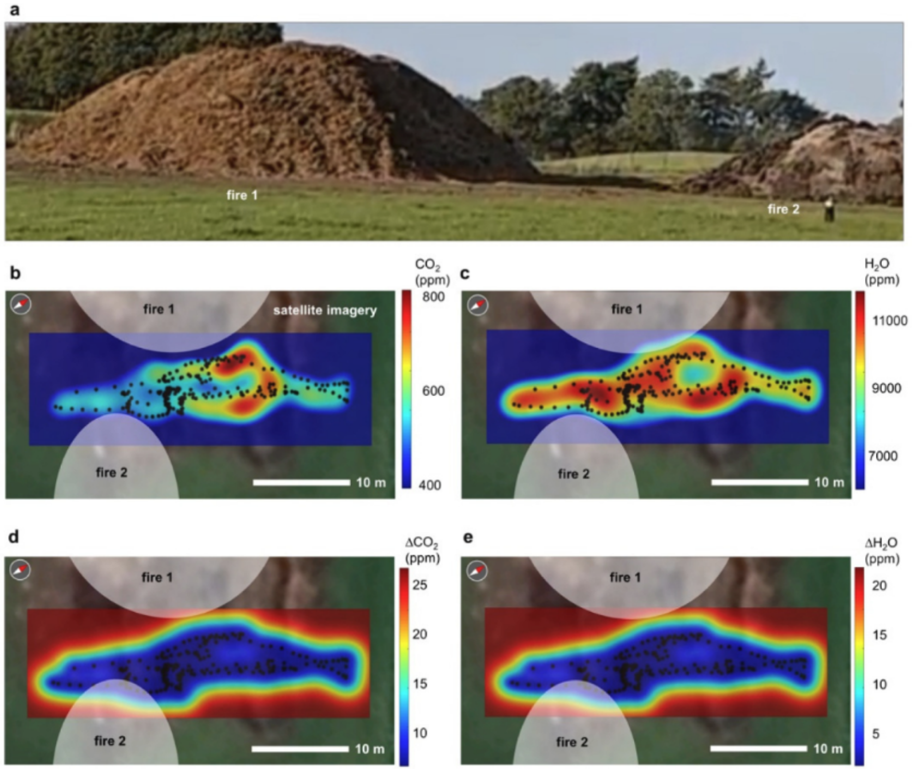
Multi-species environmental gas sensing



M. Rutkauskas, M. Asenov, S. Ramamoorthy, D.T. Reid, **Autonomous multi-species environmental gas sensing using drone-based Fourier-transform infrared spectroscopy**, *Optics Express*, 2019.

Multi-species environmental gas sensing





Conclusion and Discussion

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- Using a low fidelity simulation and domain specific assumptions (spatially invariant wind)
  -> Can lead to fast convergence and accurate localization

M. Asenov, M. Rutkauskas, D.T. Reid, K. Subr, S. Ramamoorthy, **Active localization of gas leaks using fluid simulation**, *IEEE Robotics and Automation Letters*, Vol 4(2), 2019.

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Conclusion and Discussion

- Limited data
  -> Fluid simulations incorporate useful dynamics knowledge

- In online setting running computationally expensive simulations is not feasible.
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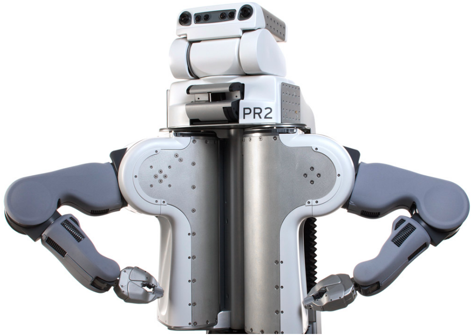
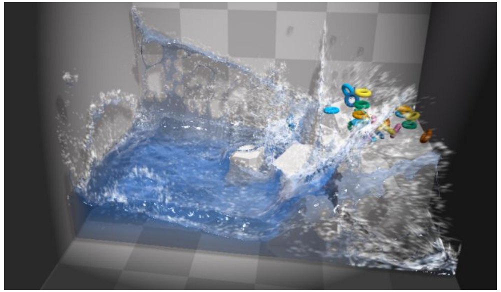
My work - using simulations as models in robotics





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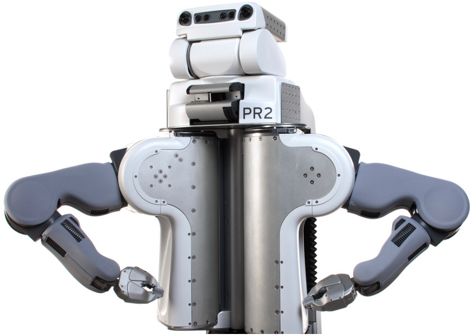

Vid2Param: Modelling of Dynamics Parameters from Video

Martin Asenov, Michael Burke, Daniel Angelov, Todor Davchev, Kartic Subr and Subramanian Ramamoorthy

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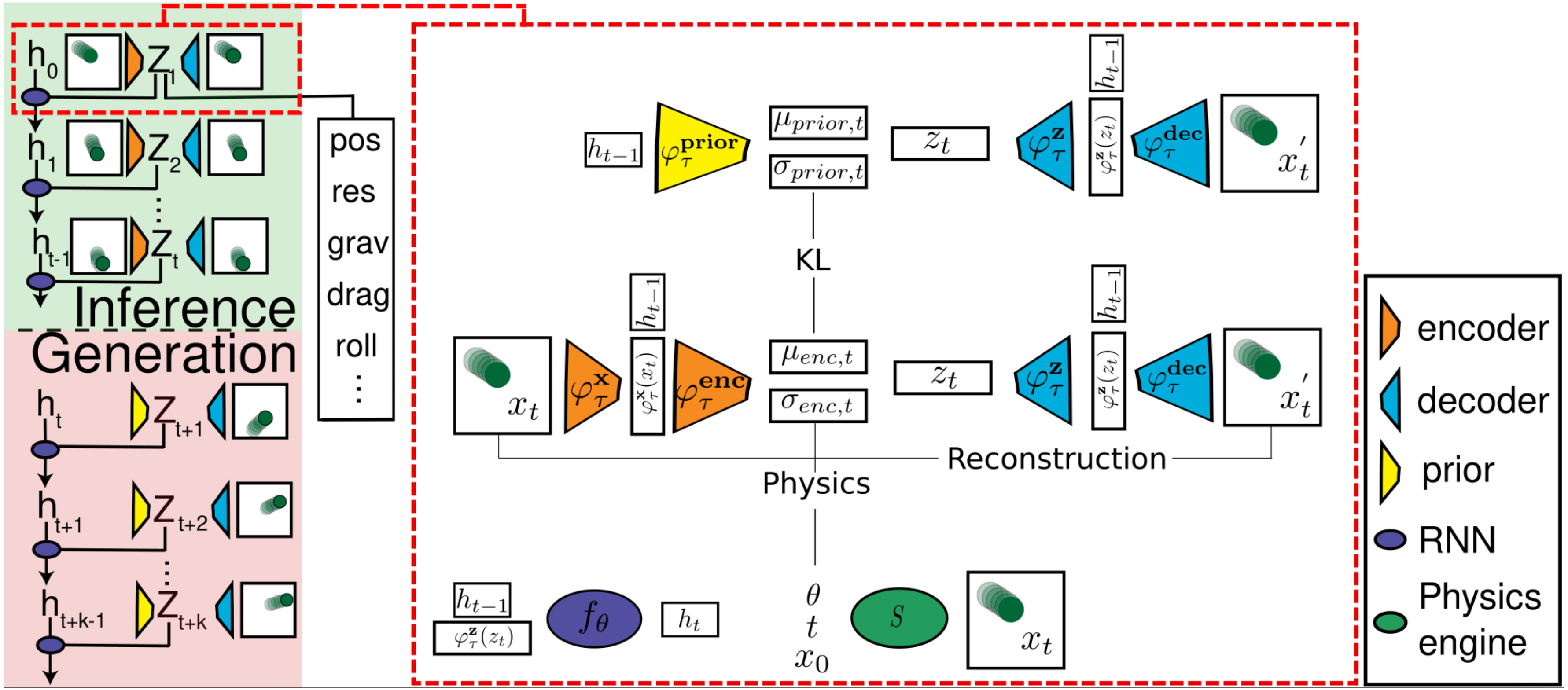
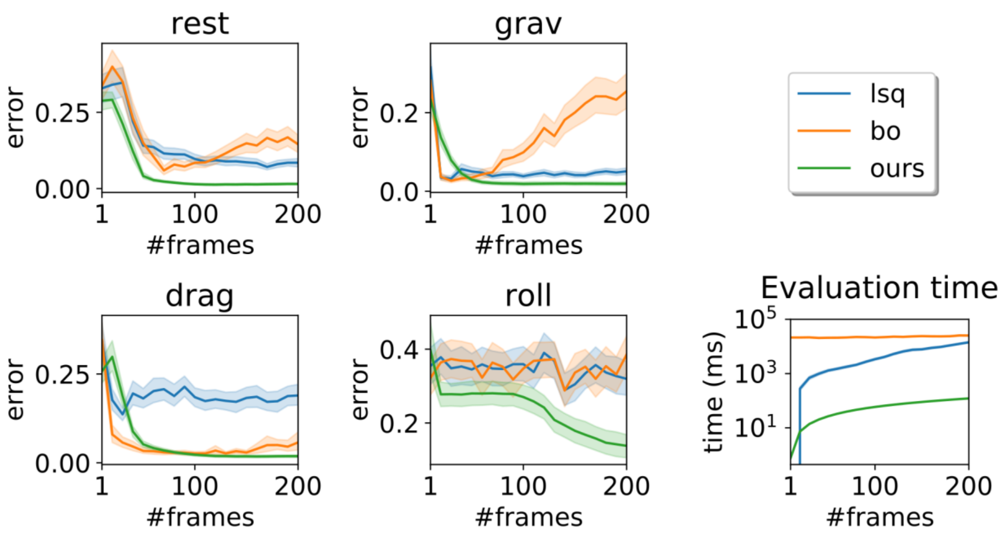
Reasoning about dynamics from video

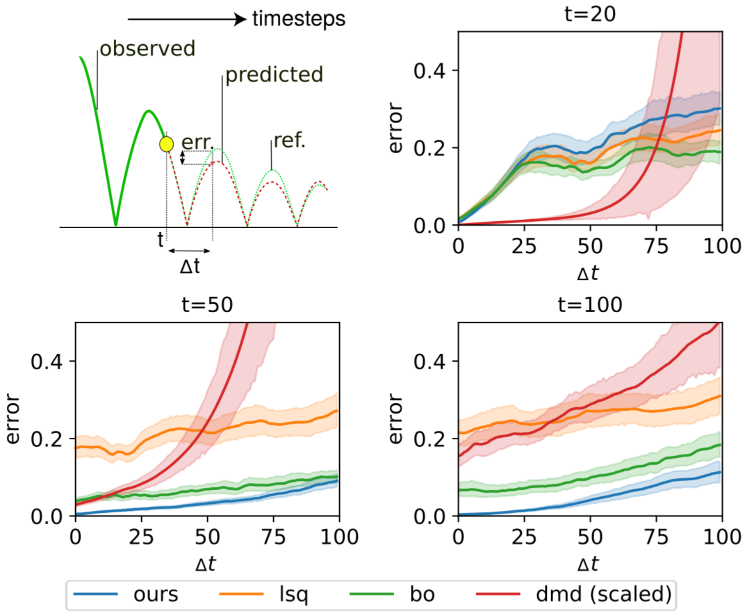
Model overview



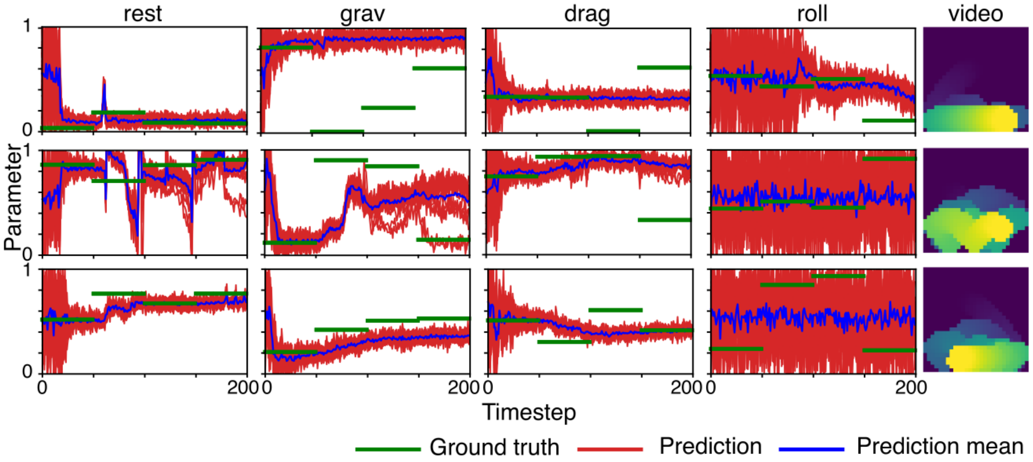
Results - SysID and forward predictions

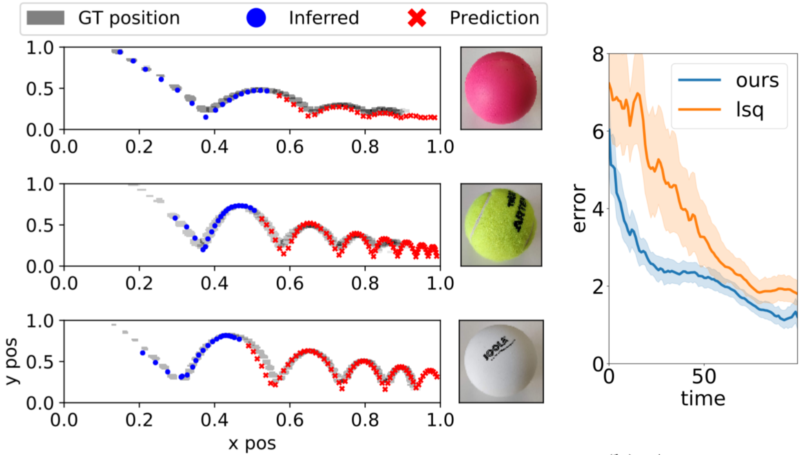


(a) Accuracy (b) Speed



Results - varying parameters and real videos

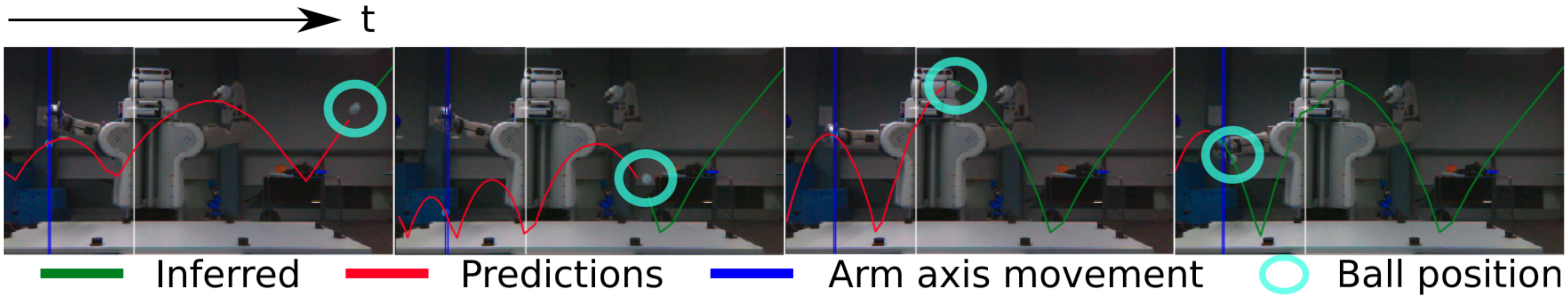




(a) Convergence

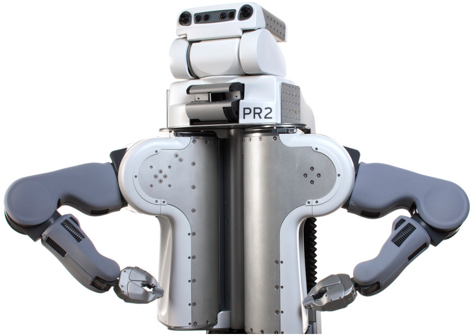
(b) Accuracy

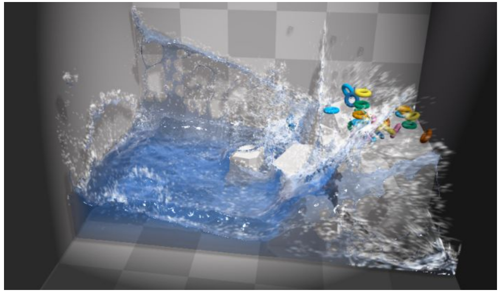
Results - robot experiments



Random Policy	8/35 (23%)
Random Policy (2x)	10/35 (29%)
Vid2Param	**27/35 (77%)**

My work - using simulations as models in robotics





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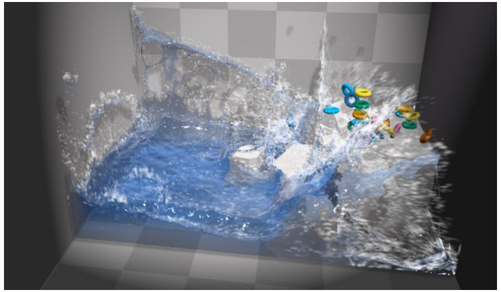

SuctionBot: Autonomous suction of fluids for medical applications (ongoing)

Martin Asenov, Kartic Subr and Subramanian Ramamoorthy

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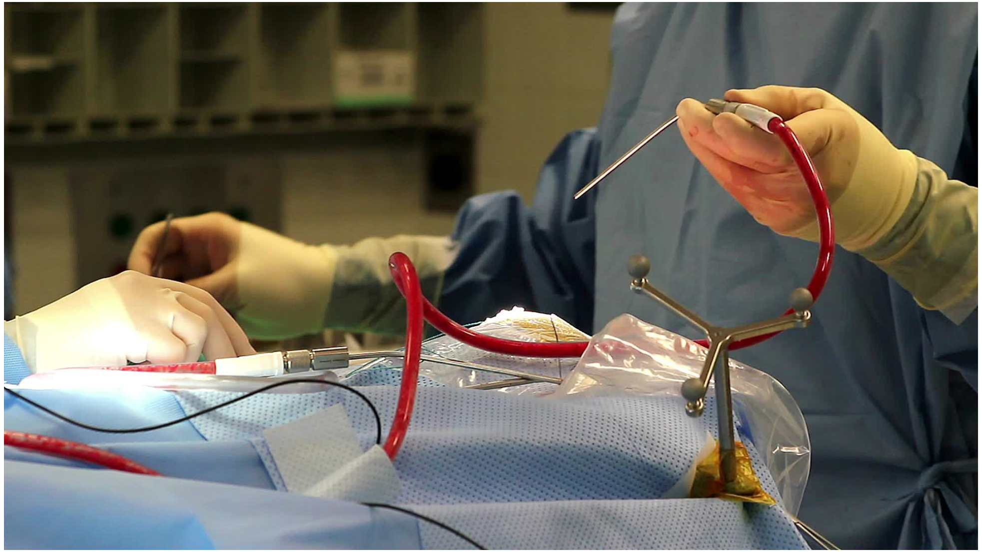
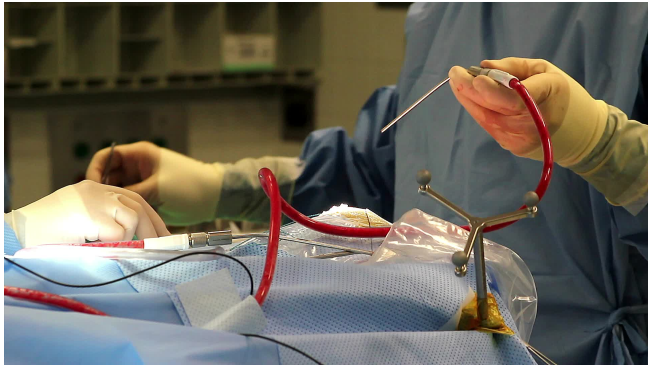
Motivation

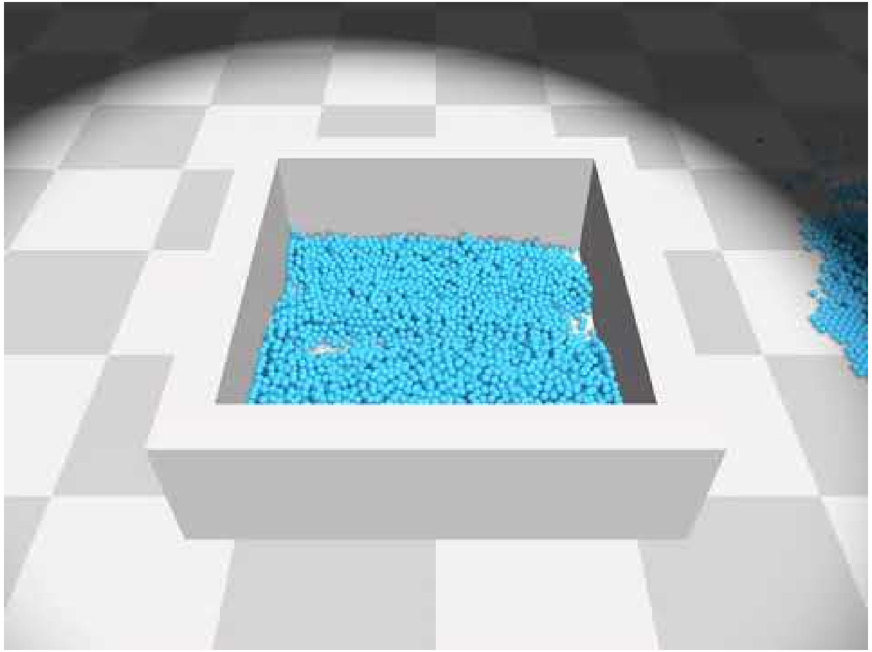


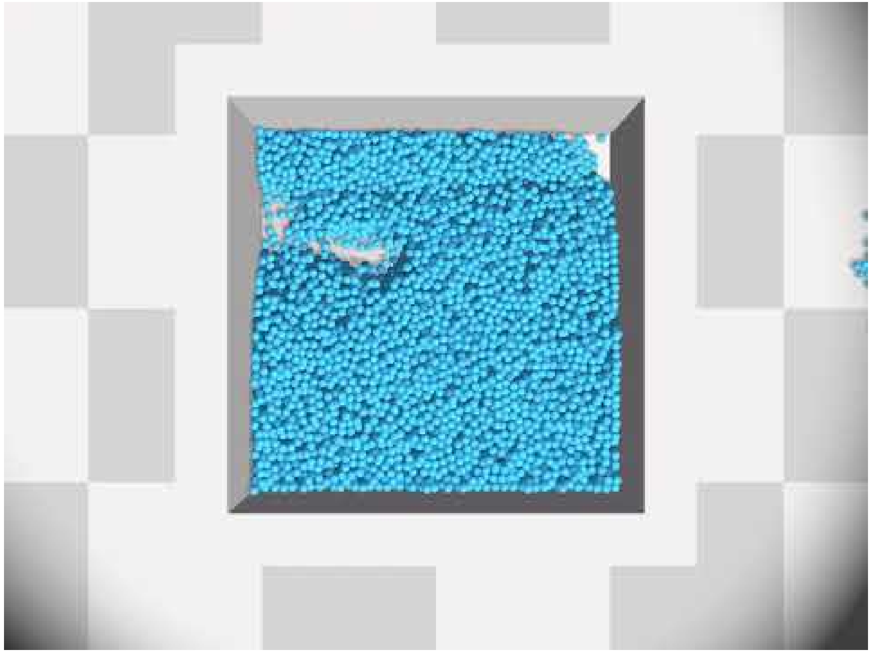
Challenging for a robot?



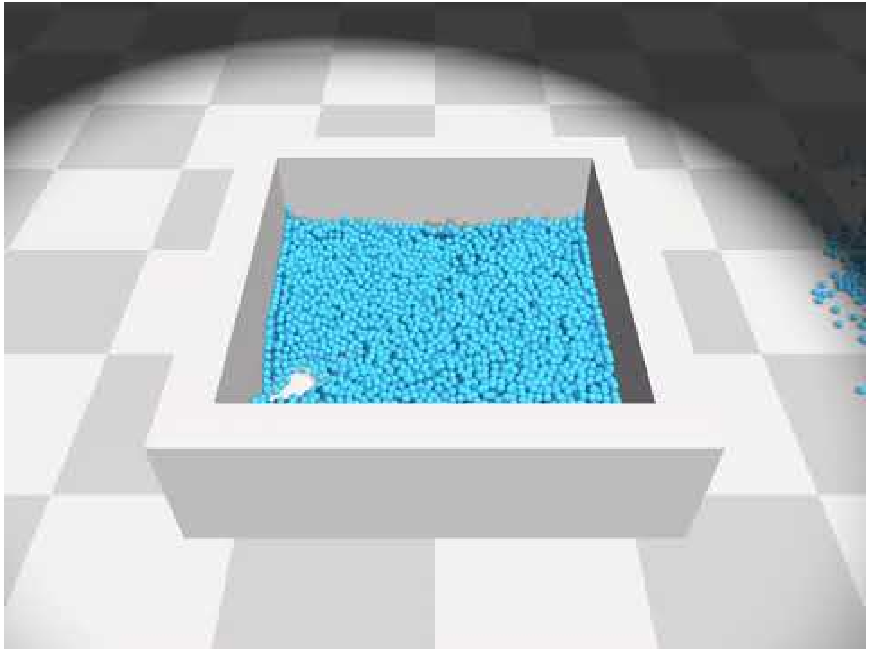
?

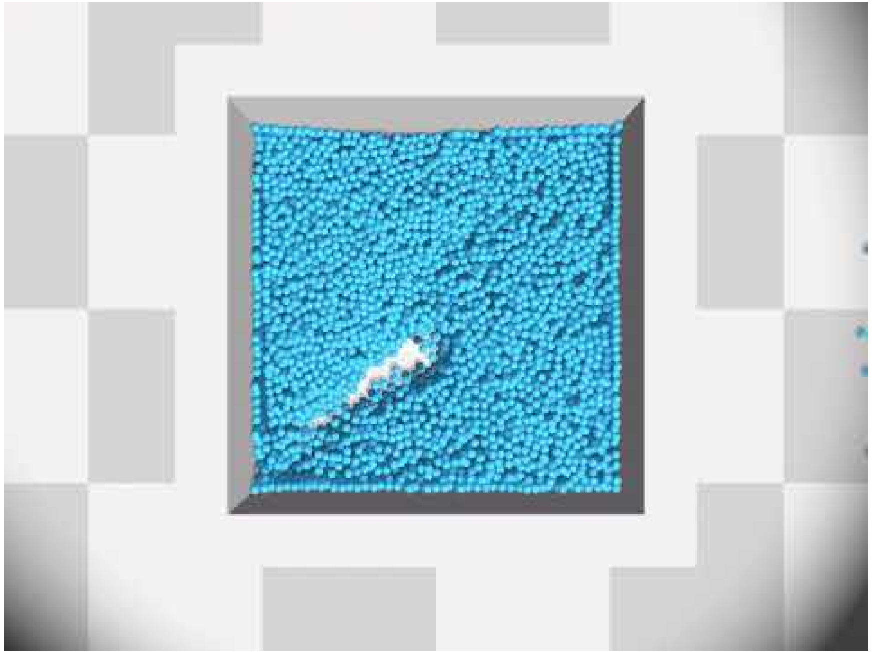
Conclusion



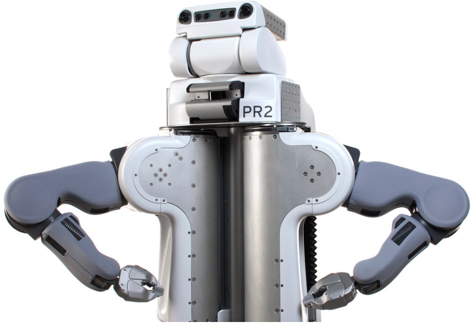


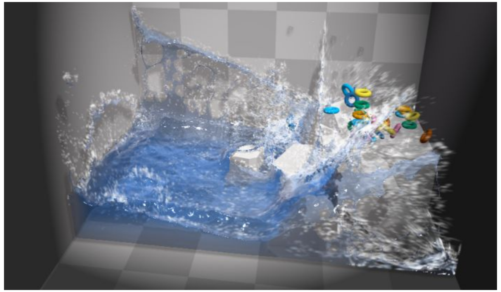
Conclusion





Conclusion - find out more on www.masenov.com





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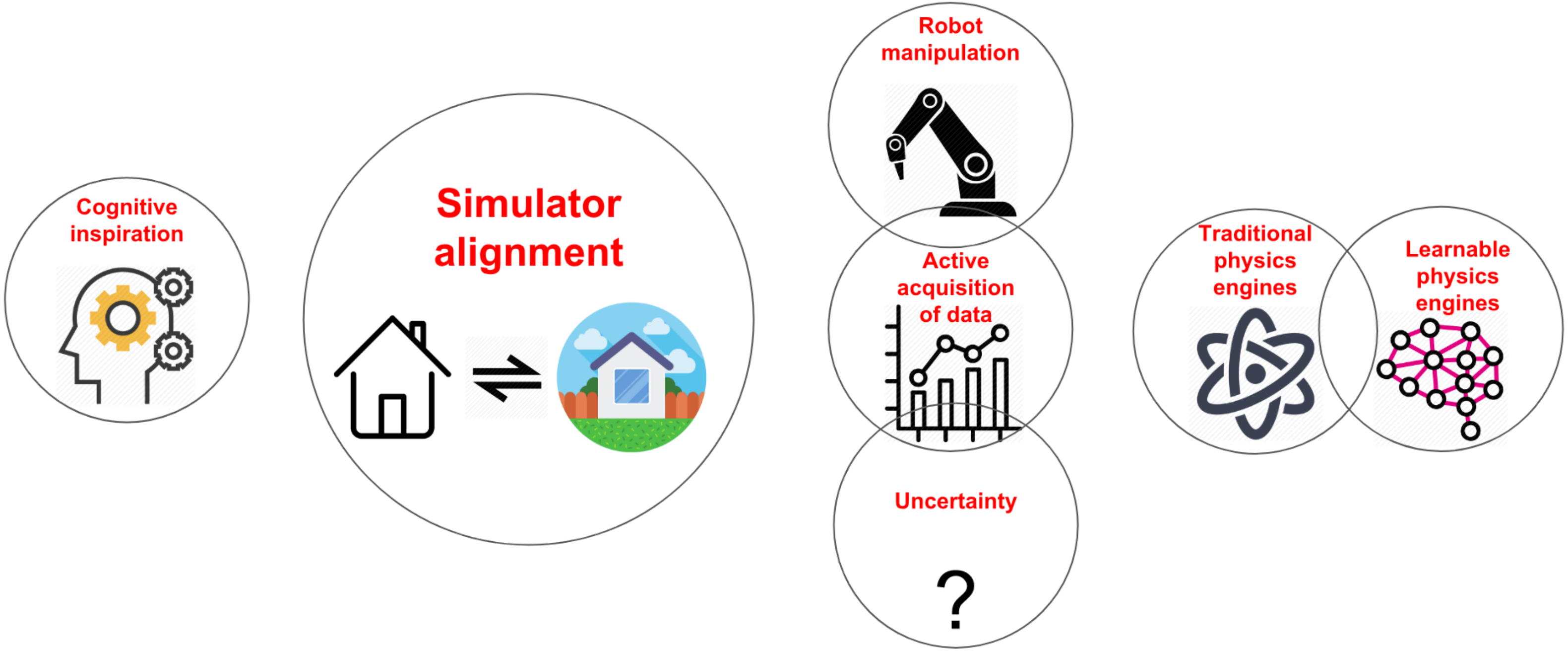

Robotics can mitigate the lack of experience of manipulating objects we have as people by learning policies in simulator, while accounting for the mismatch with respect to the real world.