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Modelling and sensor planning for environmental monitoring with gas sensors

Achim J. Lilienthal et al.

toc

Jan 18, 2023 / MRO@ISOCS WS / ajl©2023

MOBILE ROBOTICS & OLFACTION

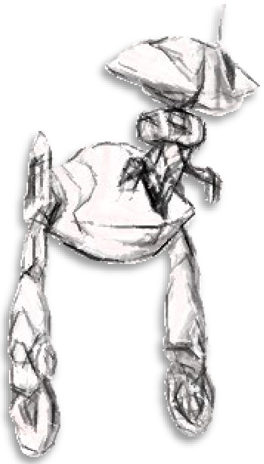
MODELLING AND SENSOR PLANNING FOR ENVIRONMENTAL MONITORING WITH GAS-SENSITIVE MOBILE ROBOTS

Achim J. Lilienthal et al.

Jan 18, 2023 / MRO@ISOCS WS / ajl©2023

AGENDA

MR&O MOBILE ROBOTICS & OLFACTION



INTRODUCTION

[1] WHY SHOULD ROBOTS SENSE GASES?

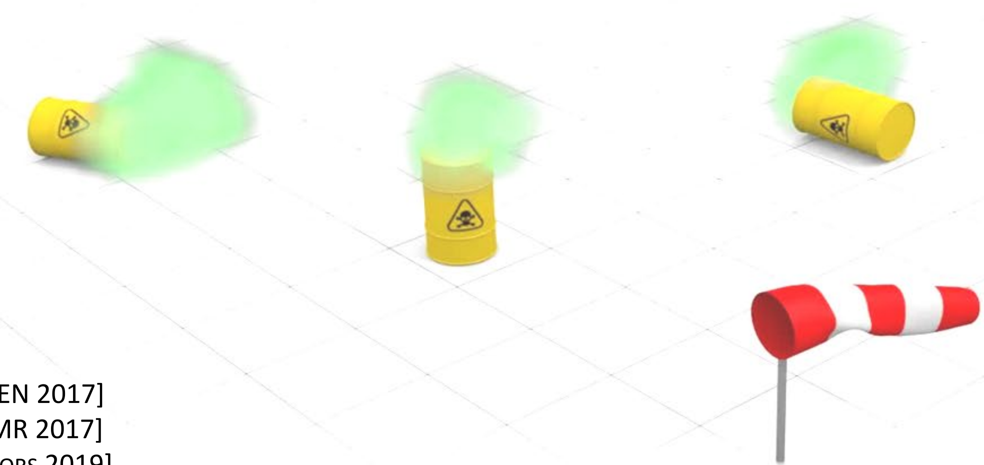
A Catastrophy in Baden-Baden (1973)

A Catastrophy in Baden-Baden (1973)

A CATASTROPHY IN BADEN-BADEN (1973)

Dedicated Mobile Gas-Sensitive Robots

- Emergency & Security
  - Firefighting, **Search and Rescue, Leak detection,** …



Video courtesy of
Thomas Wiedemann (DLR)
Dr. Dmitriy Shutin (DLR)

[Wiedemann et al., ISOEN 2017]
[Wiedemann et al., ECMR 2017]
[Wiedemann et al., Sensors 2019]
[Wiedemann et al., RAS 2019]

DLR

Dedicated Mobile Gas-Sensitive Robots

- Emergency & Security
  - **Firefighting**, Search and Rescue, Leak detection, …

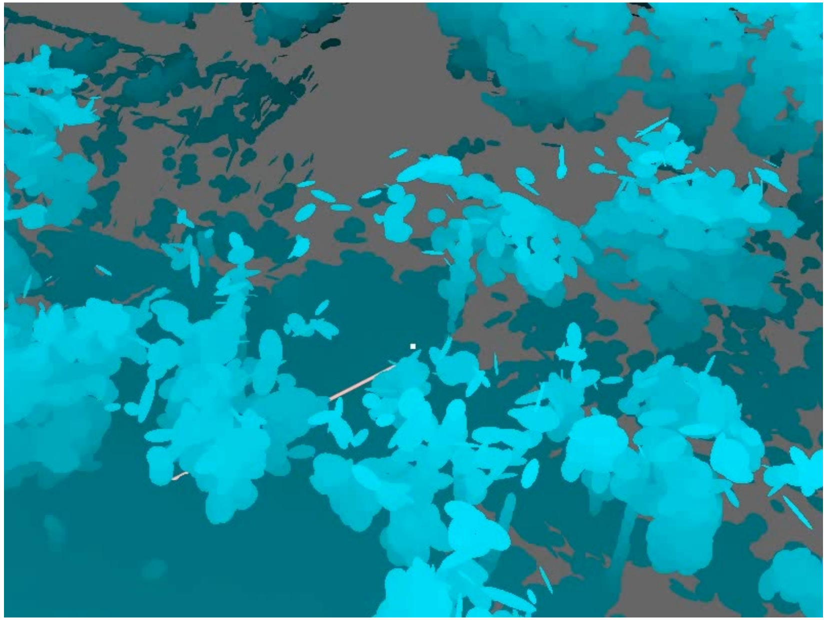
SMOKEBOT
www.smokebot.eu

Dedicated Mobile Gas-Sensitive Robots

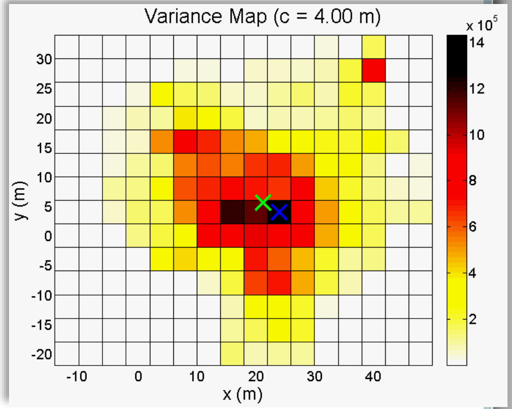
- Emergency & Security
- Surveillance, Environmental Monitoring
  - Landfills (CH_4), Vessels (SO_x), Chimneys (NH_3), Waste management sites (H_2S, malodors), Urban environments (BC, NO, NO_2, …)

DEDICATED MOBILE GAS-SENSITIVE ROBOTS

- Emergency & Security
- Surveillance, Environmental Monitoring
  - **Landfills (CH_4)**, Vessels (SO_x), Chimneys (NH_3), Waste management sites (H_2S, malodors), Urban environments (BC, NO, NO_2, …)
    - Gasbot

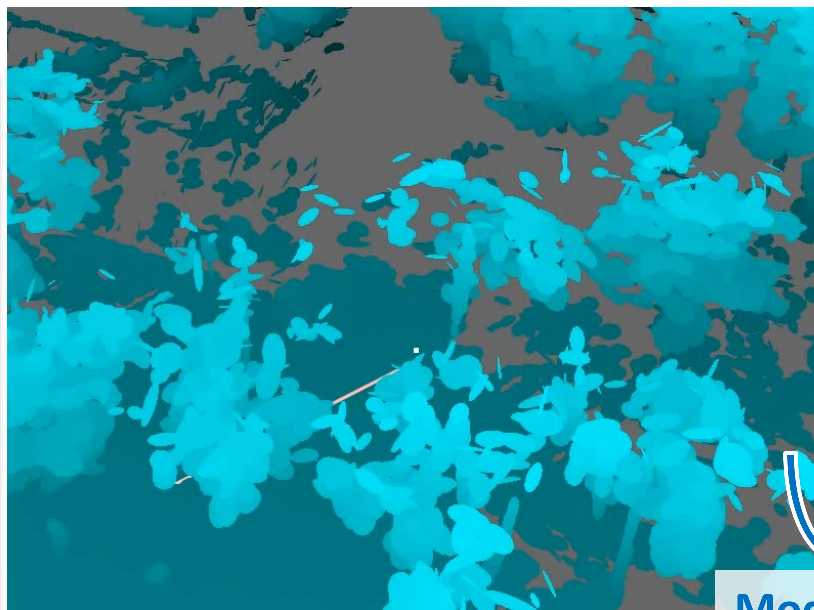


[HERNANDEZ BENNETTS ET AL., ICRA 2014]
[HERNANDEZ BENNETTS ET AL., ICRA 2013]
[HERNANDEZ BENNETTS ET AL., FNENG 2012]

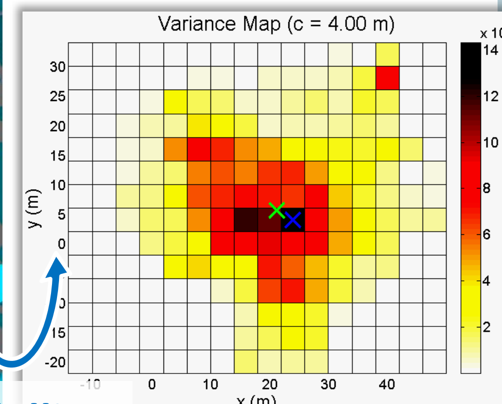


Dedicated Mobile Gas-Sensitive Robots

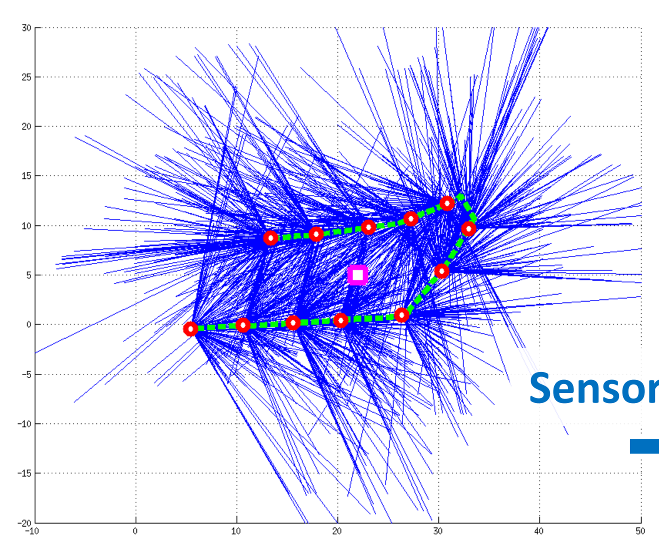
- Emergency & Security
- Surveillance, Environmental Monitoring
  - **Landfills (CH_4)**, Vessels (SO_x), Chimneys (NH_3), Waste management sites (H_2S, malodors), Urban environments (BC, NO, NO_2, …)
    - Gasbot



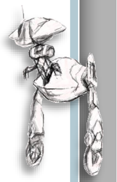
[Hernandez Bennetts et al., ICRA 2014]
[Hernandez Bennetts et al., ICRA 2013]
[Hernandez Bennetts et al., FNEng 2012]



Modelling



GAS-SENSITIVE ROBOTS



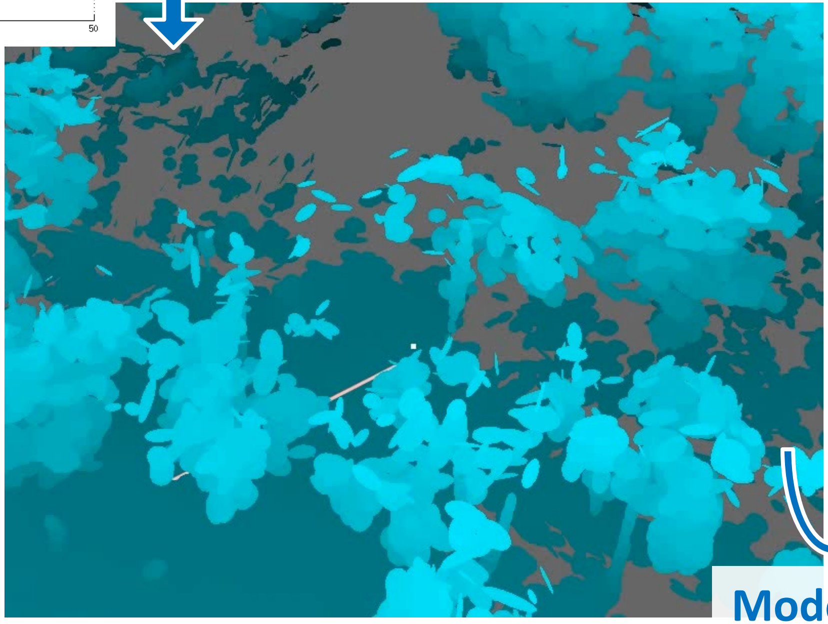
curity

ironmental Monitoring

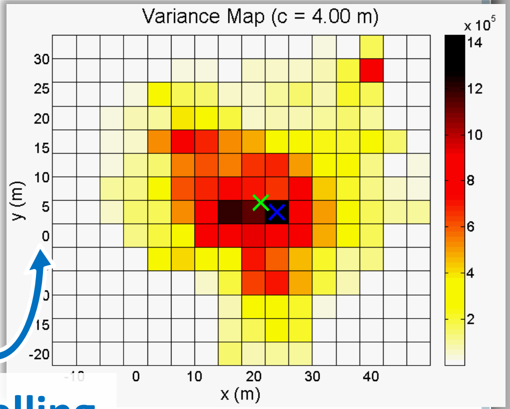
Sensor Planning

SO_x), Chimneys (NH_3), Waste management

rs), Urban environments (BC, NO, NO_2, …)



[HERNANDEZ BENNETTS ET AL., ICRA 2014]
[HERNANDEZ BENNETTS ET AL., ICRA 2013]
[HERNANDEZ BENNETTS ET AL., FNENG 2012]



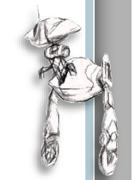
Modelling

toc

Dedicated Mobile Gas-Sensitive Robots

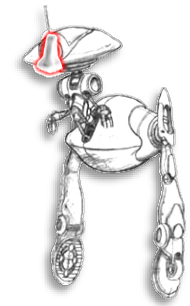
- Emergency & Security
- Surveillance, Environmental Monitoring
- Regulatory Monitoring of Industrial Sites
  - Agriculture (CO_2), Mining (CH_4), Biogas refinery, …

Dedicated Mobile Gas-Sensitive Robots



- Emergency & Security
- Surveillance, Environmental Monitoring
- Regulatory Monitoring of Industrial Sites
- Scientific Missions
  - Volcanos (CO_2, SO_2), Atmospheric chemistry (Vertical profiles of PM, O_3, CO_2), Forest ecosystems (biogenic VOCs)

APPLICATION AREAS OF GAS-SENSITIVE MOBILE ROBOTS



- Dedicated Mobile Gas-Sensitive Robots – Conclusions
  - Specifically designed for a "gas task"
  - Typically using expensive sensors matching the task

[REGGENTE ET AL., CHEMENGTRANS 2010]
[TRINCAVELLI ET AL., IROS 2008]

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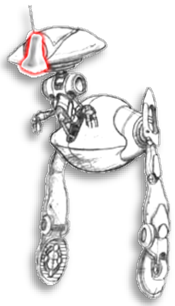
Application Areas of Gas-Sensitive Mobile Robots

APPLICATION AREAS OF GAS-SENSITIVE MOBILE ROBOTS



- Dedicated Mobile Gas-Sensitive Robots
  - Specifically designed for a "gas task"
  - Typically use expensive sensors matching the task

Application Areas of Gas-Sensitive Mobile Robots

- Dedicated Mobile Gas-Sensitive Robots
  - Specifically designed for a "gas task"
  - Typically use expensive sensors matching the task
- Gas Sensing as Addition to Available Mobile Robots
  - Detect leaking gas pipes
  - Detect fire at its initial stage (CO)
  - Monitor pollutants in the environment
  - Dedicated or broad-spectrum sensors "<=" Electronic Nose

Application Areas of Gas-Sensitive Mobile Robots

- Dedicated Gas-Sensitive Robots
  - Specifically designed for a "gas task"
  - Typically use expensive sensors matching the task

- Gas Sensing as Addition to Available Robots
  - Monitor pollutants in the environment

http://www.dustbot.org

[Reggente et al., ChemEngTrans 2010]
[Trincavelli et al., IROS 2008]

DustBot Project

- DustClean

DustBot Project

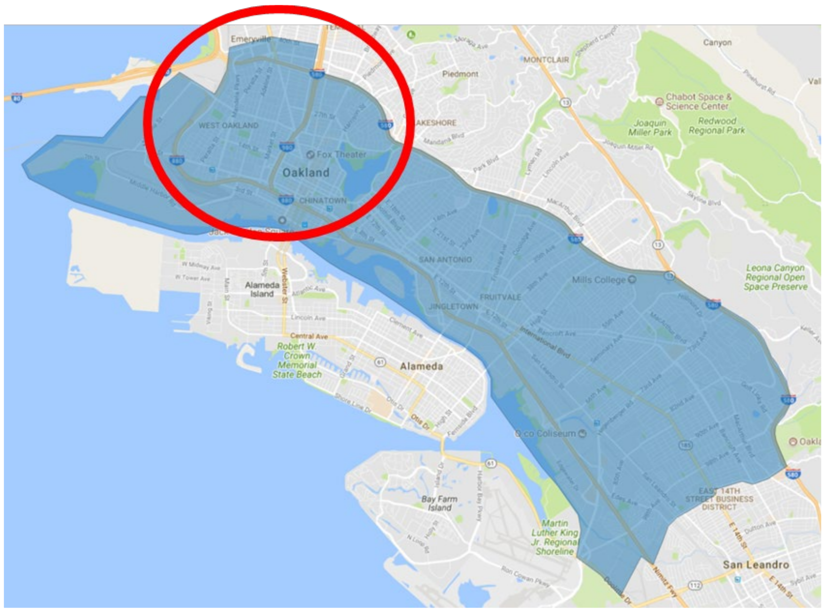
- DustClean
- DustCart

Similar video at:
https://youtu.be/v=Fd__eI9NbGo

"ALSO" GAS-SENSITIVE MOBILE ROBOTS

- Surveillance, Environmental Monitoring – Passive Mobility
  - Landfills (CH_4), Vessels (SO_x), Chimneys (NH_3), Waste management sites (H_2S, malodors), **Urban environments (BC, NO, NO_2, …)**
    - Urban scale + passive mobility (Oakland measurement campaigns [2015-2017])

[APTE ET AL., ENV. SCI. TECH. 2017]
[MESSIER ET AL., ENV. SCI. TECH. 2018]



Robots should smell!

… and there should be smelling robots!

Introduction

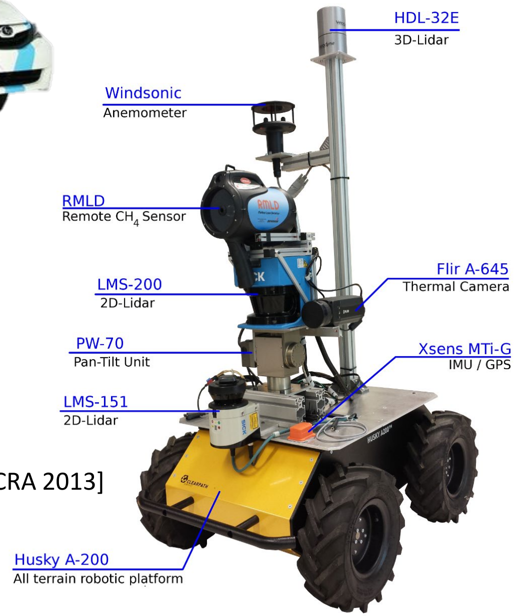
[2] Mobile Robot Olfaction

Mobile Robot Olfaction

[Apte et al., Env. Sci. Tech. 2017]

[Messier et al., Env. Sci. Tech. 2018]

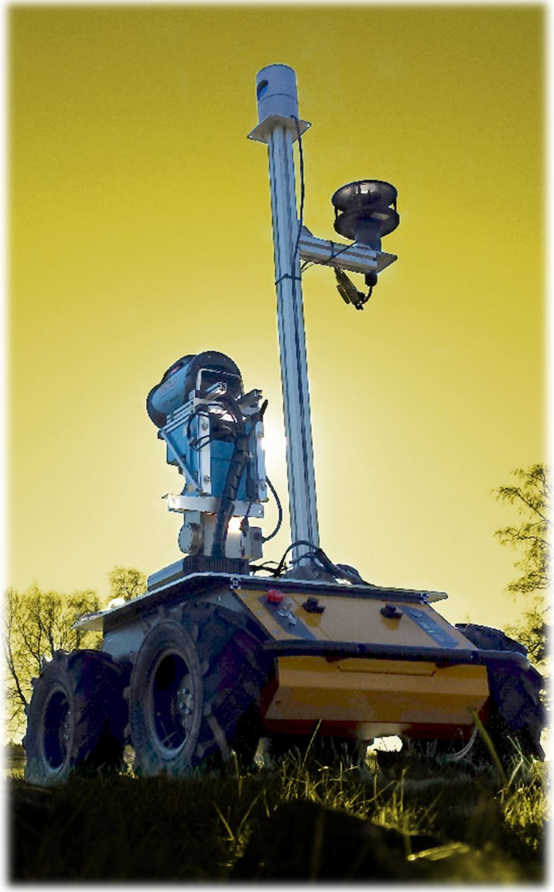
www.edf.org/climate/methanemaps/partnership



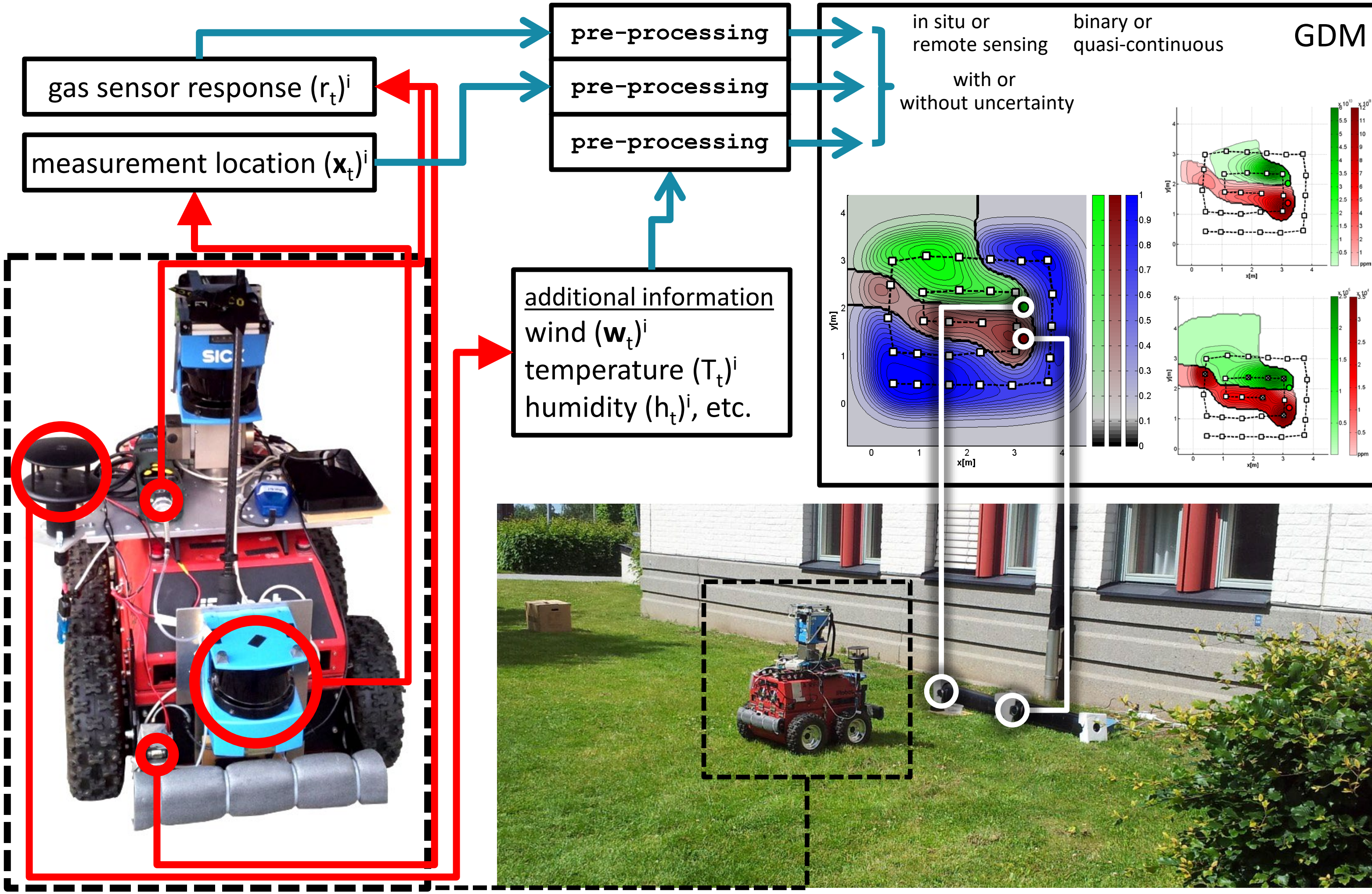
[Hernandez Bennetts et al., ICRA 2013]

Application Areas of Gas-Sensitive Mobile Robots

- Advantages of Mobile Robot Environmental Monitoring?
  - <u>Robots</u> vs. humans, dogs, etc.
    - Can be exposed to dangerous environments
    - Can carry out more than one task simultaneously
    - Accurate positioning (onboard computation)
  - <u>Mobile</u> robots vs. sensor networks
    - Higher spatial resolution
    - Fewer sensors needed
    - Adaptability
    - Rapid deployment



Components of Typical Mobile Robot Olfaction Solutions



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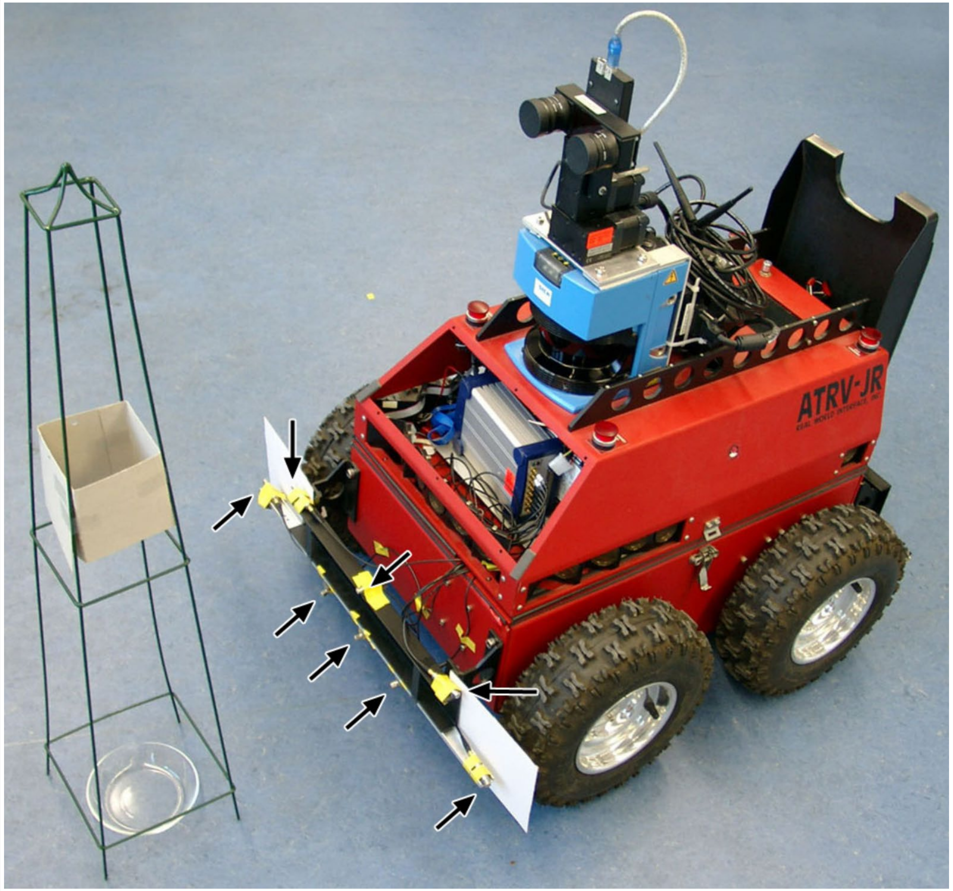
Early Research Work

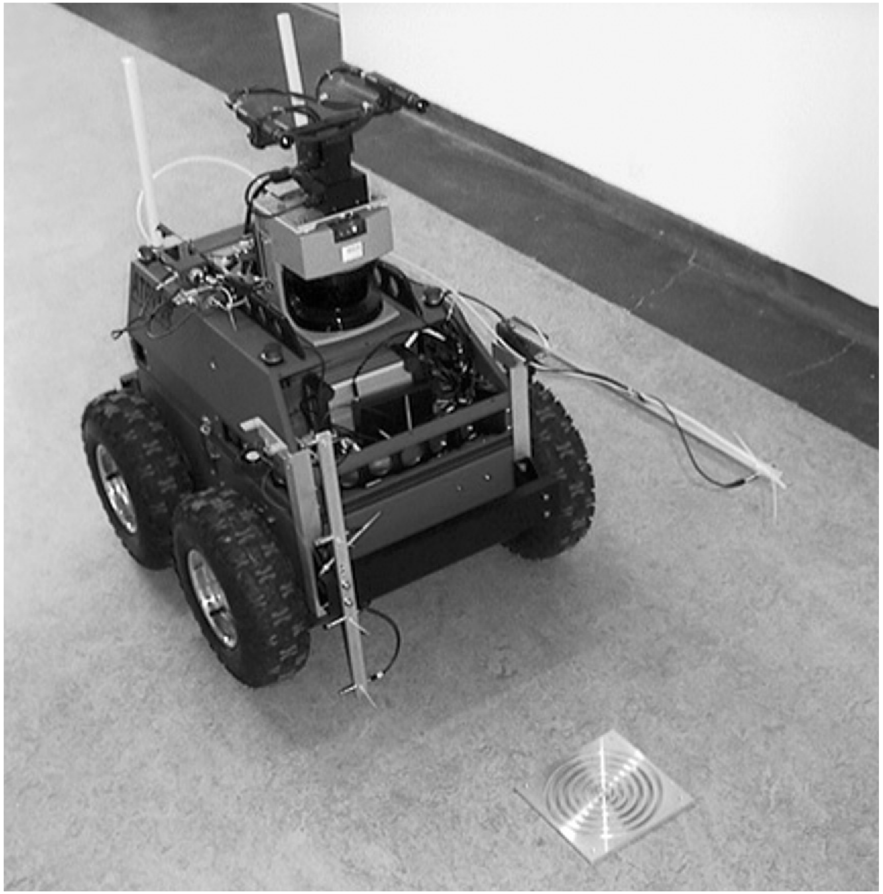
[3] 1D Gas Source Localization

To Begin With …

To Begin With – Get a Robot to Move ...

To Begin With – … and add Gas Sensors

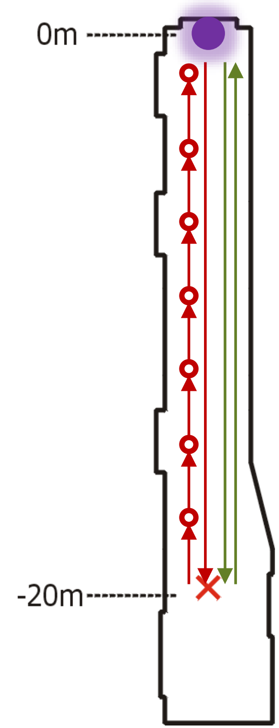




"1D" GAS SOURCE LOCALISATION

[Lilienthal et al., ICRA, 2001]

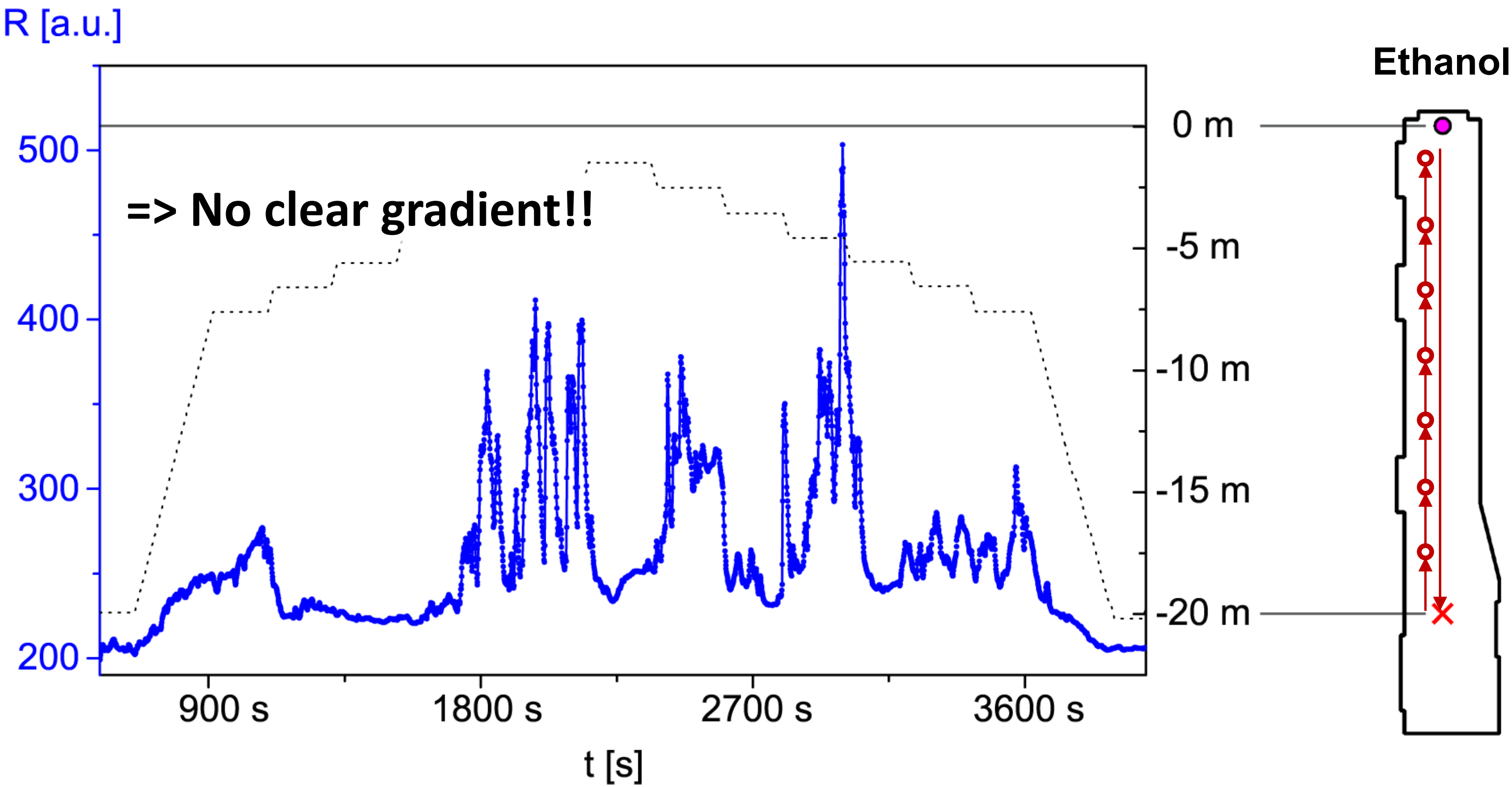
- Environment
  - Corridor ("1D")
  - No ventilation
  - No people passing by
- Gas Source
  - Bowl filled with ethanol
  - Different intensities (20 cm², 60 cm², 130 cm²)
- Driving Modes
  - Stop-Sense-Go
  - Constant Velocity Sensing



"1D" GAS SOURCE LOCALISATION

[Lilienthal et al., ICRA, 2001]

- Stop-Sense-Go



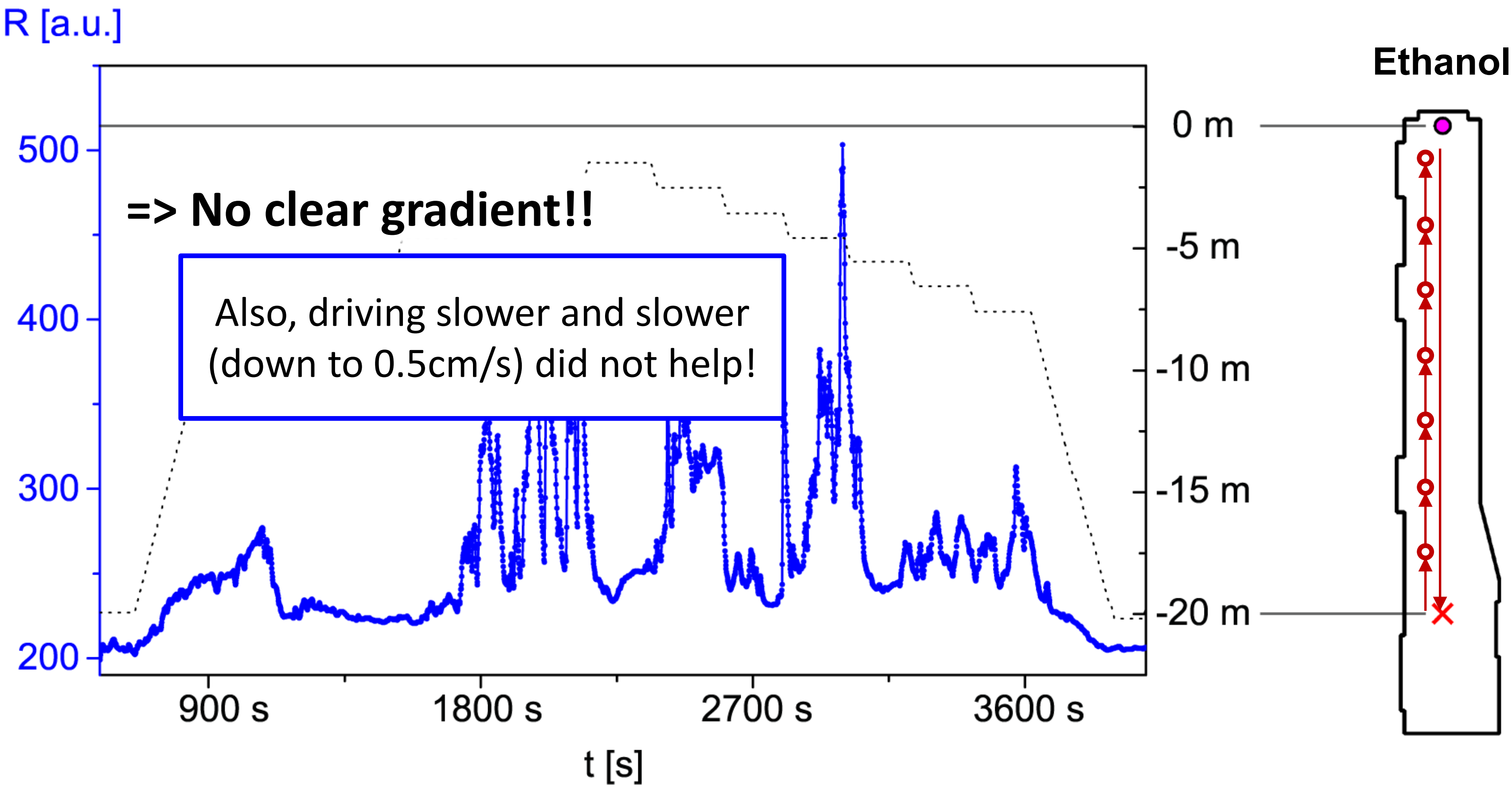
"1D" Gas Source Localisation

[Lilienthal et al., ICRA, 2001]

- Stop-Sense-Go

=> No clear gradient!!

Also, driving slower and slower (down to 0.5cm/s) did not help!



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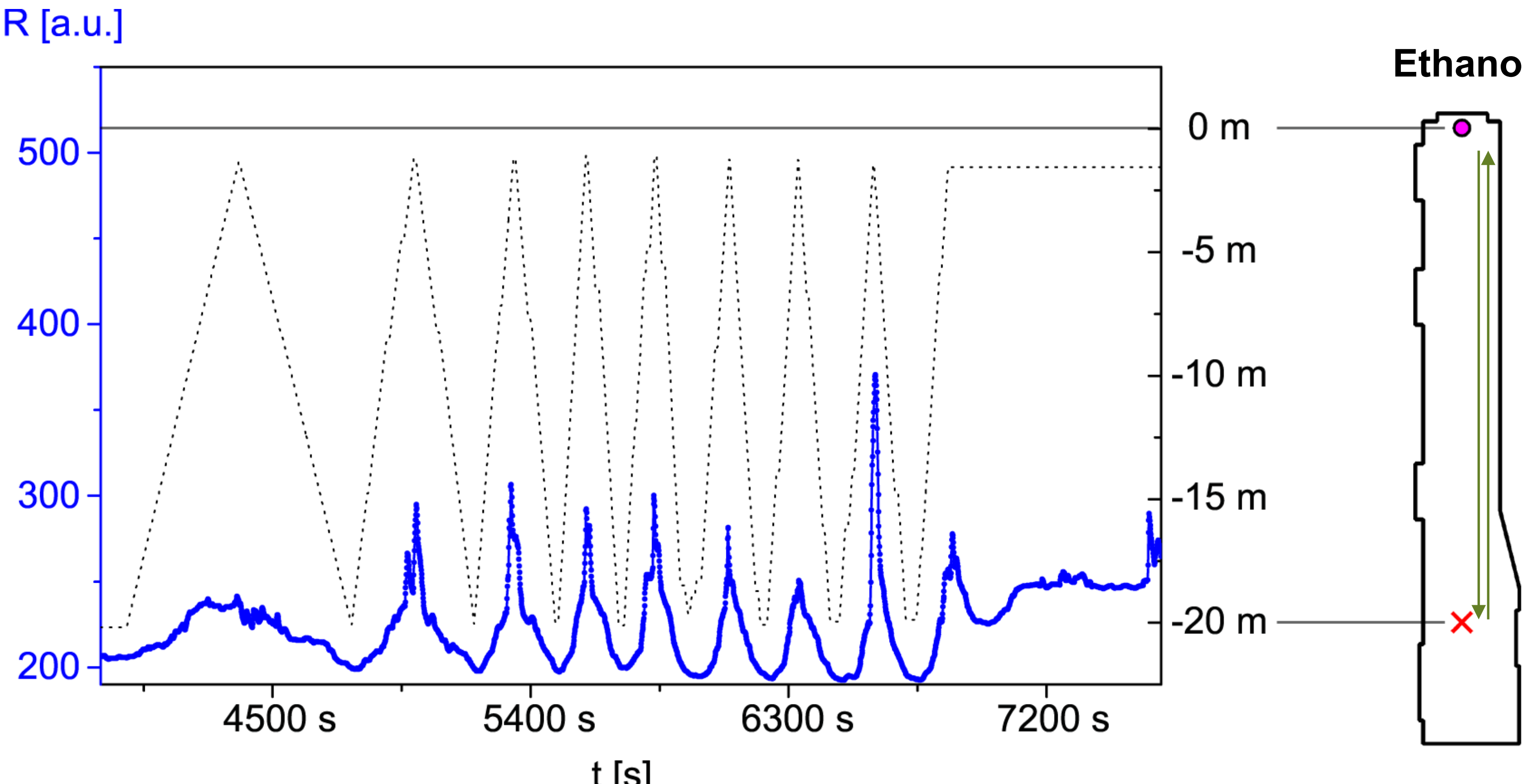
"1D" GAS SOURCE LOCALISATION

[Lilienthal et al., ICRA, 2001]

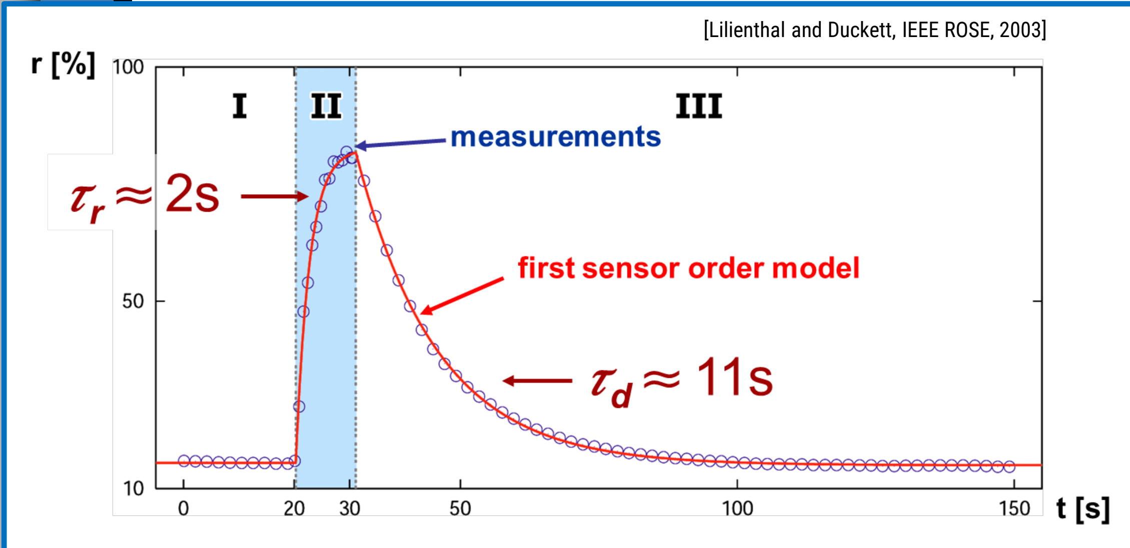
- Constant Velocity Sensing (> 5 cm/s)!



"1D" Gas Source Localisation

[Lilienthal et al., ICRA, 2001]

- Close Interaction with the Sensing Strategy
  - Constant Velocity Sensing (CVS):
    - Peaks often indicate source proximity (accuracy ≈ 1m)
  - Stop-Sense-Go (SSG):
    - Peaks are randomly distributed
  - SSG results could not be improved
    - … by using a pumped cell
    - … by using PC fans

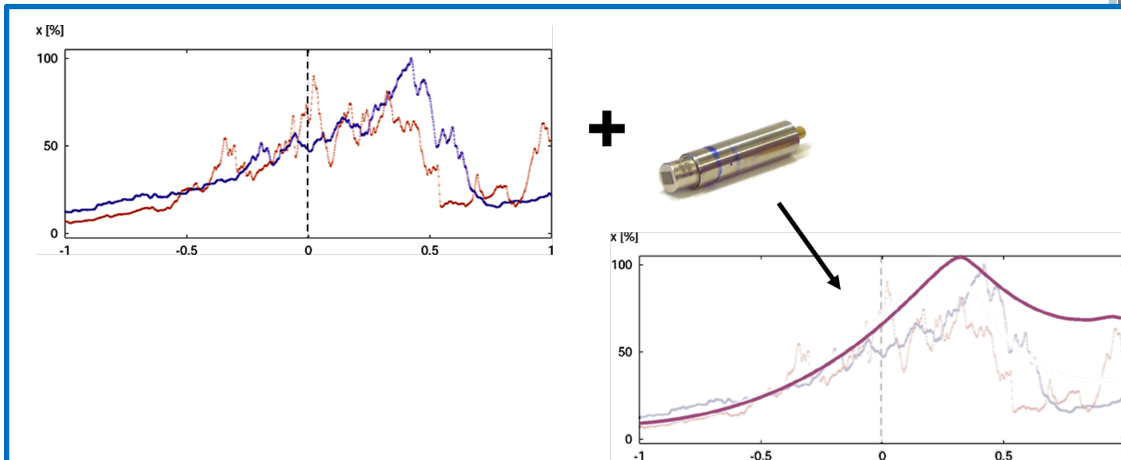


[Lilienthal et al., ICRA, 2001]

Strategy

ccuracy ≈ 1m)

- Explanation of the "CVS Effect"?
  - => MOX Sensors average due to their long decay time
  - **=> Spatio-temporal averaging if MOX sensors are carried by a moving robot!**



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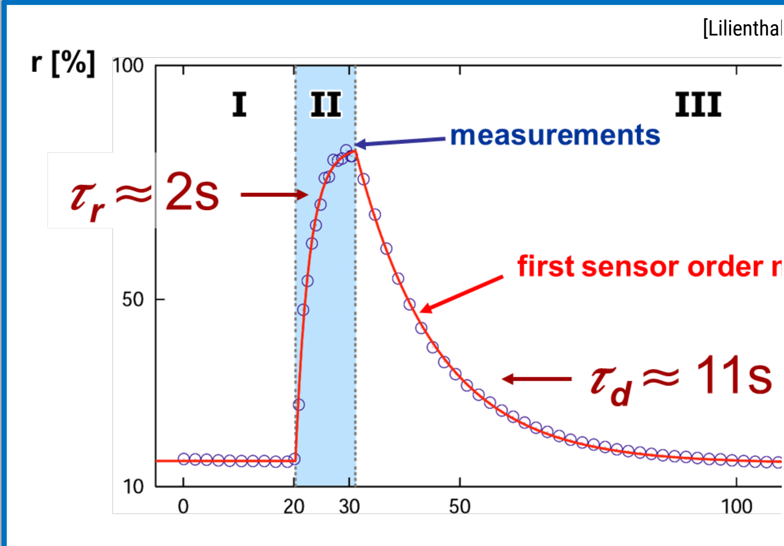
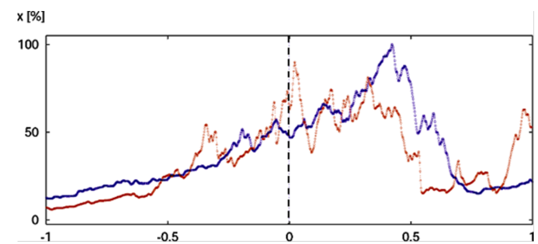
MOBILE ROBOTICS & OLFACTION

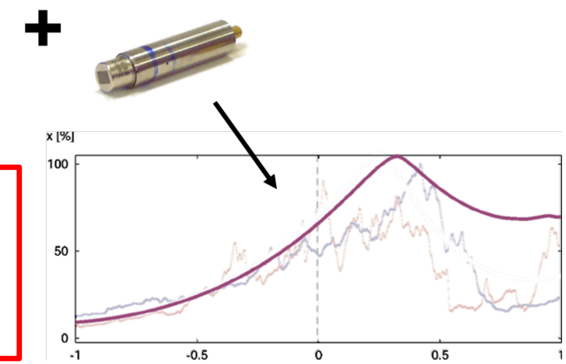
MODELLING AND SENSOR PLANNING FOR ENVIRONMENTAL MONITORING WITH GAS SENSORS

Achim J. Lilienthal et al.



- Explanation of the "C
  - => MOX Sensors aver
  - **=> Spatio-temporal averaging if MOX sensors are carried by a moving robot!**





=> Sensing strategy is important!
=> Spatial and temporal interpolation of instantaneous measurements may be a good idea!

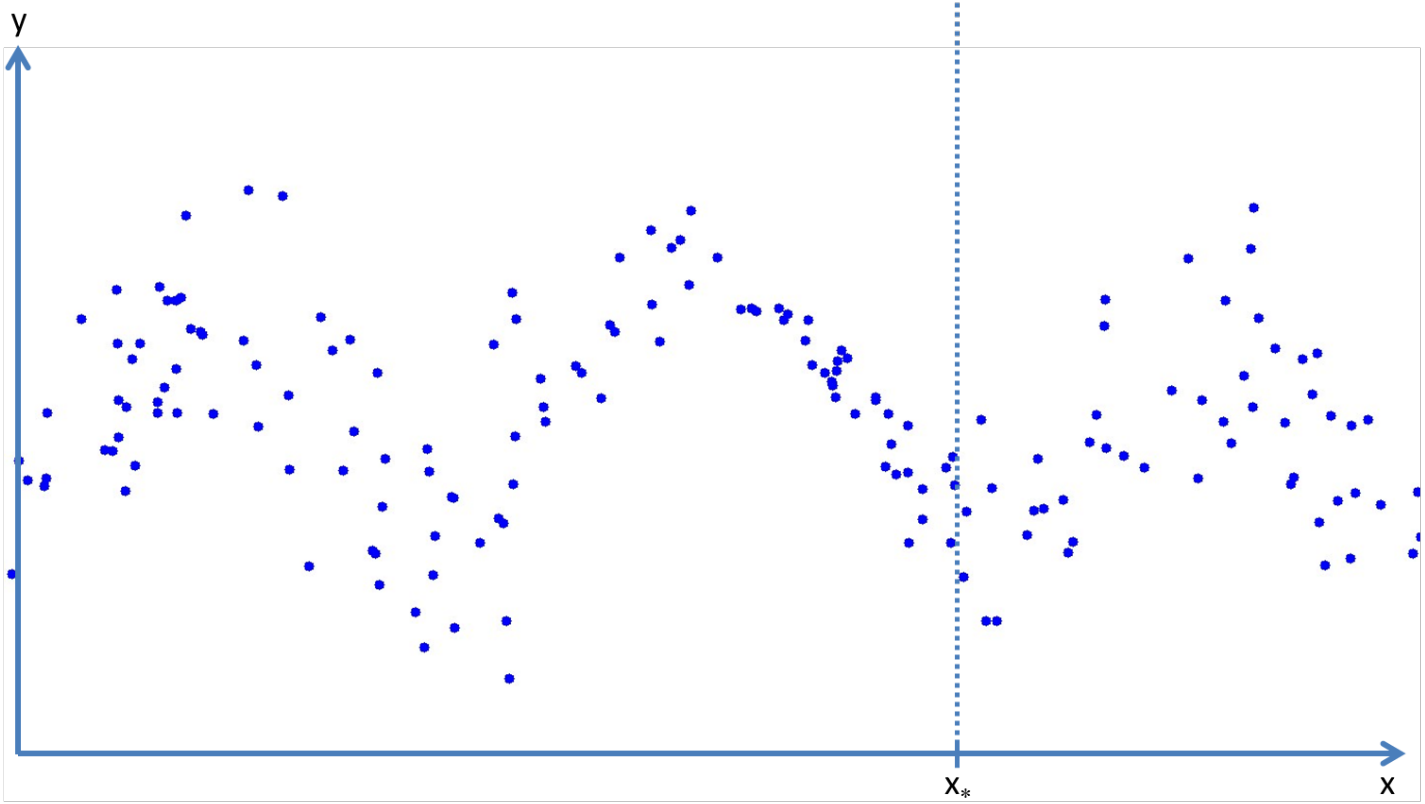
Early Research Work

[4] Kernel DM for GDM

[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

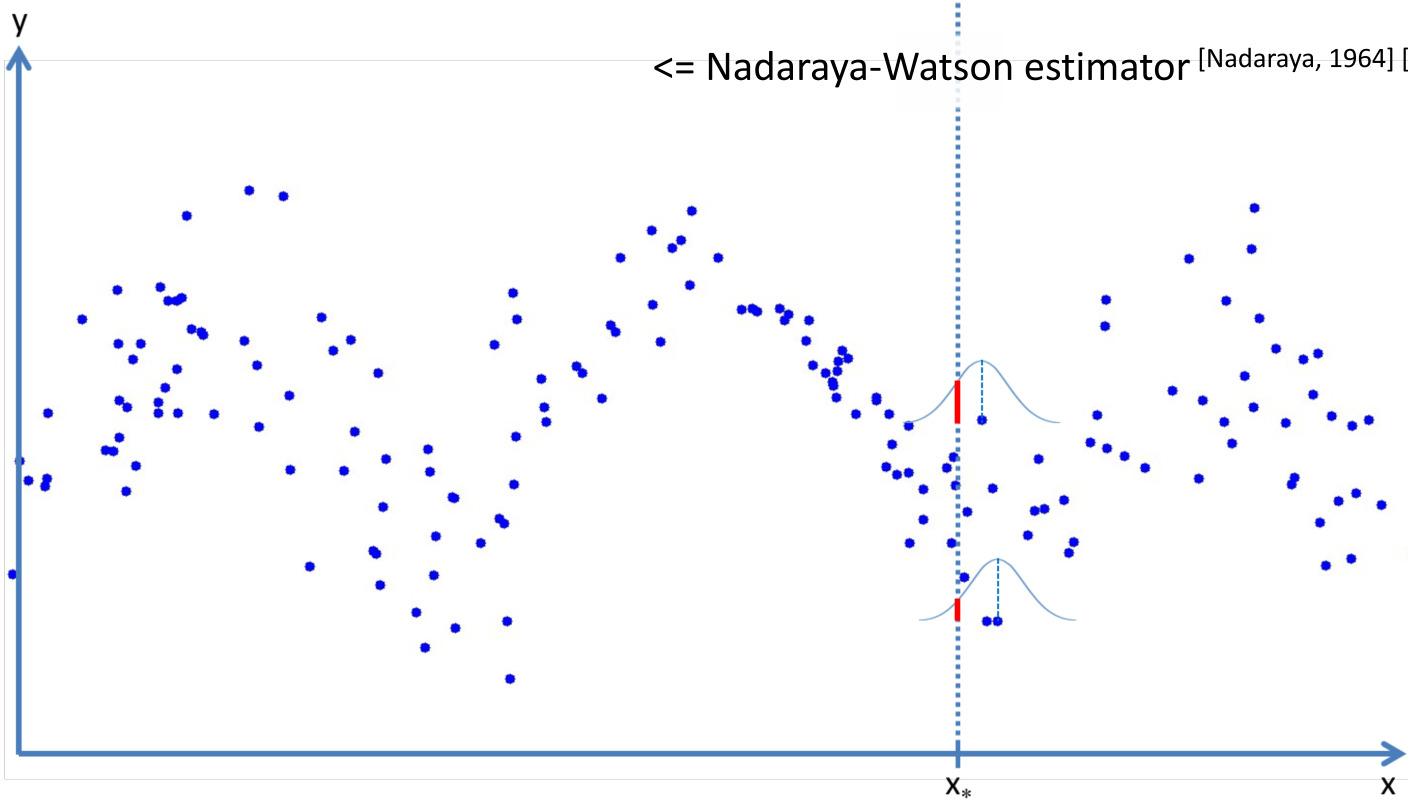
- Importance of spatial interpolation
  - Kernel DM – 1D Example



[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

- Importance of spatial interpolation
  - Kernel DM – 1D Example

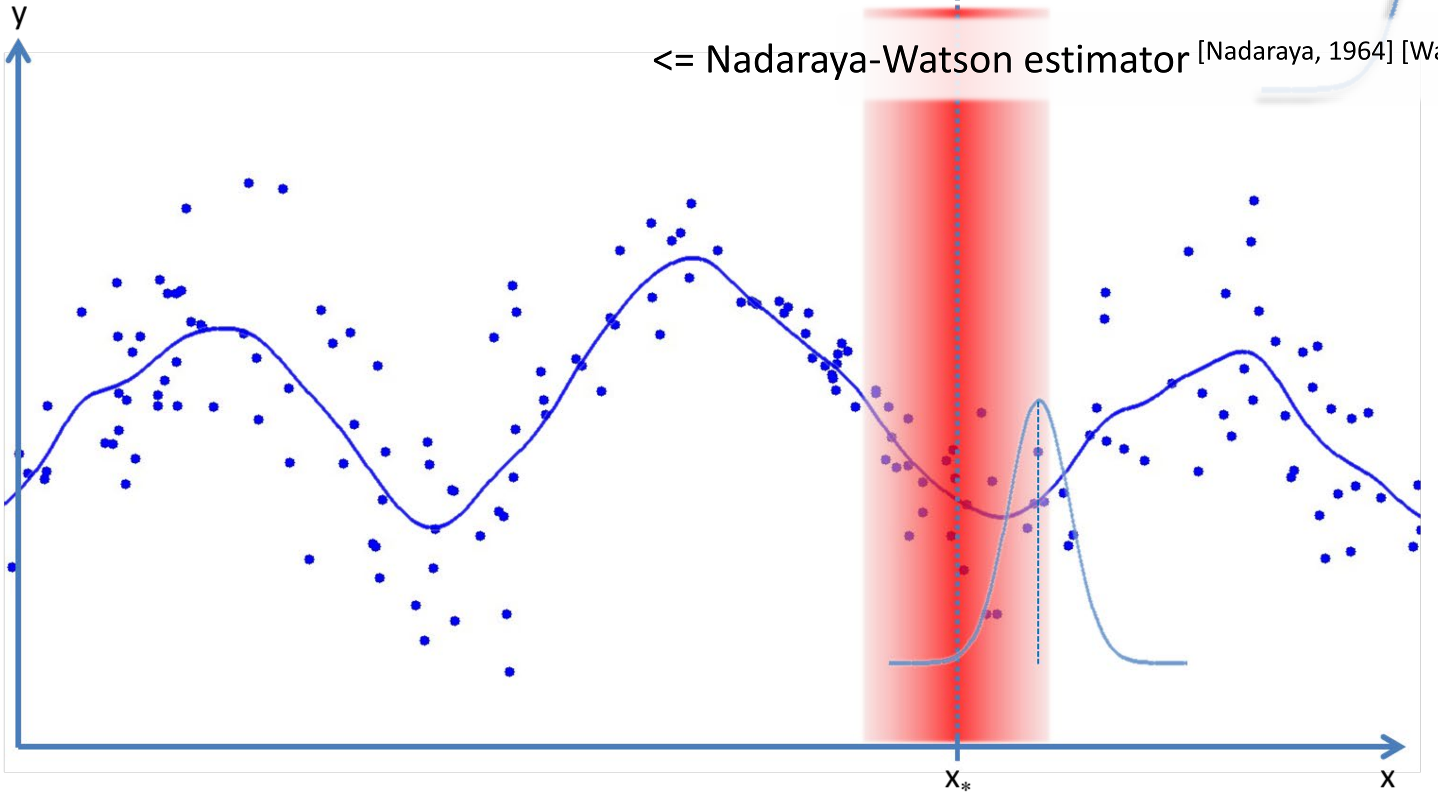


[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 0.75)

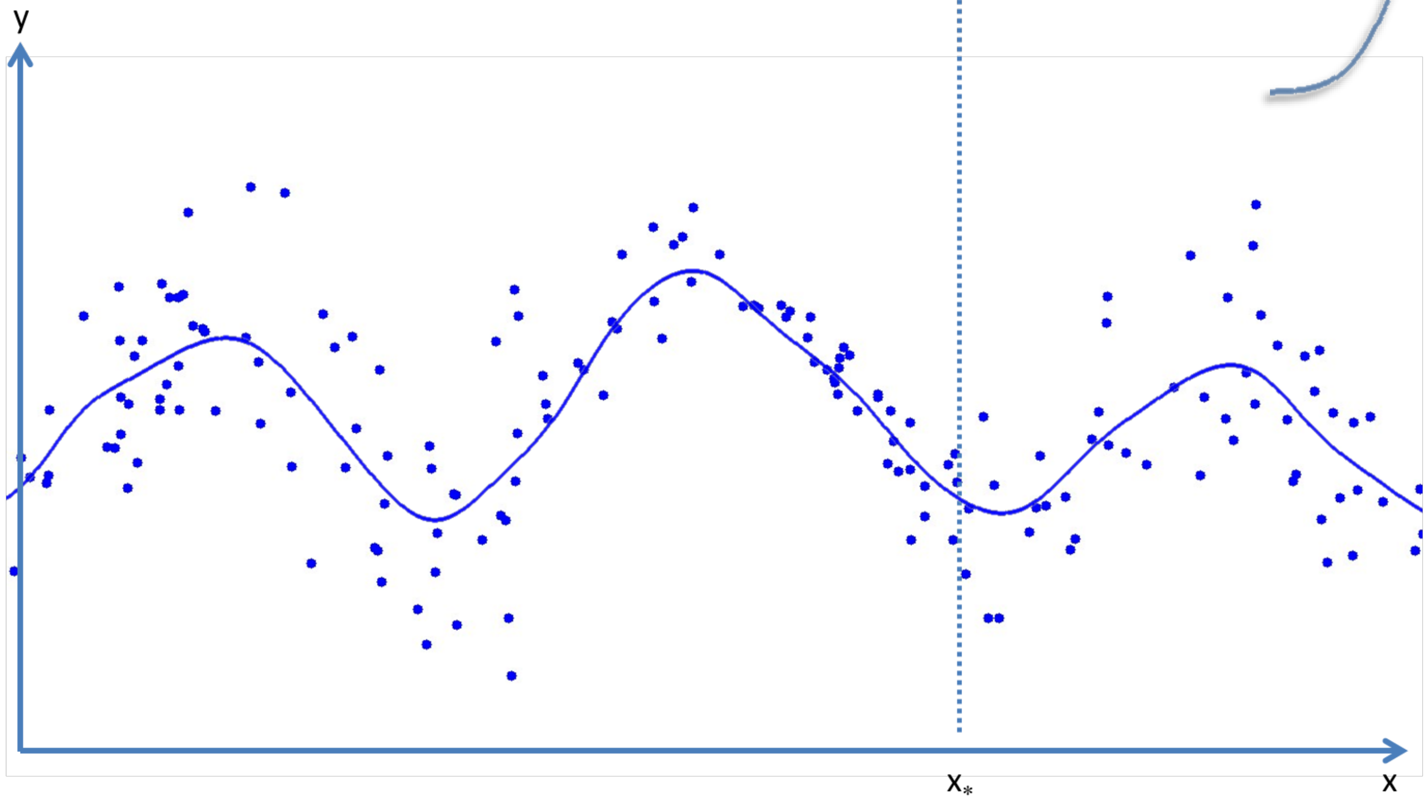
<= Nadaraya-Watson estimator [Nadaraya, 1964] [Watson, 1964]



[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

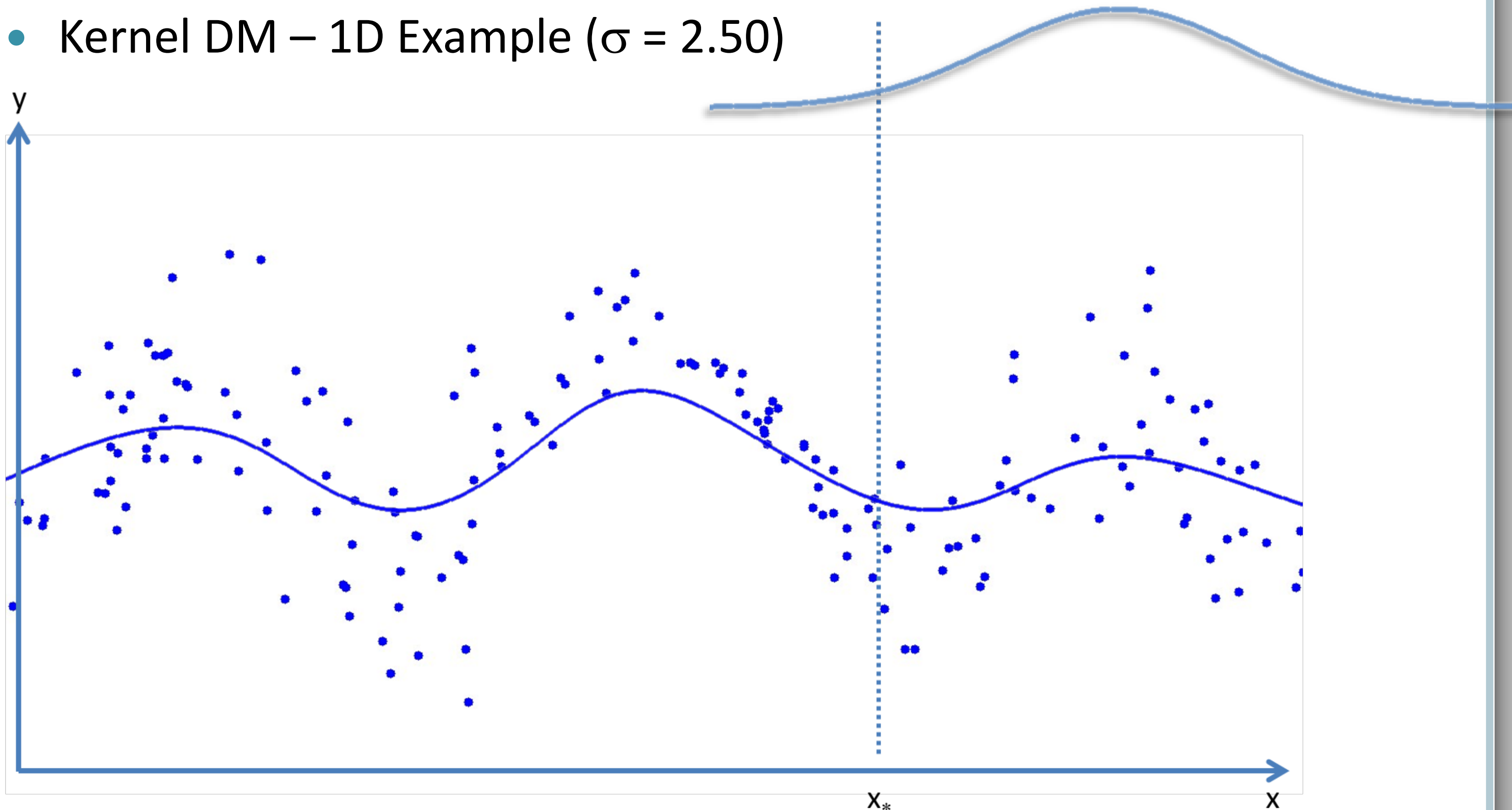
- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 1.00)



[Lilienthal & Duckett, RAS 2004]

Kernel DM for GDM

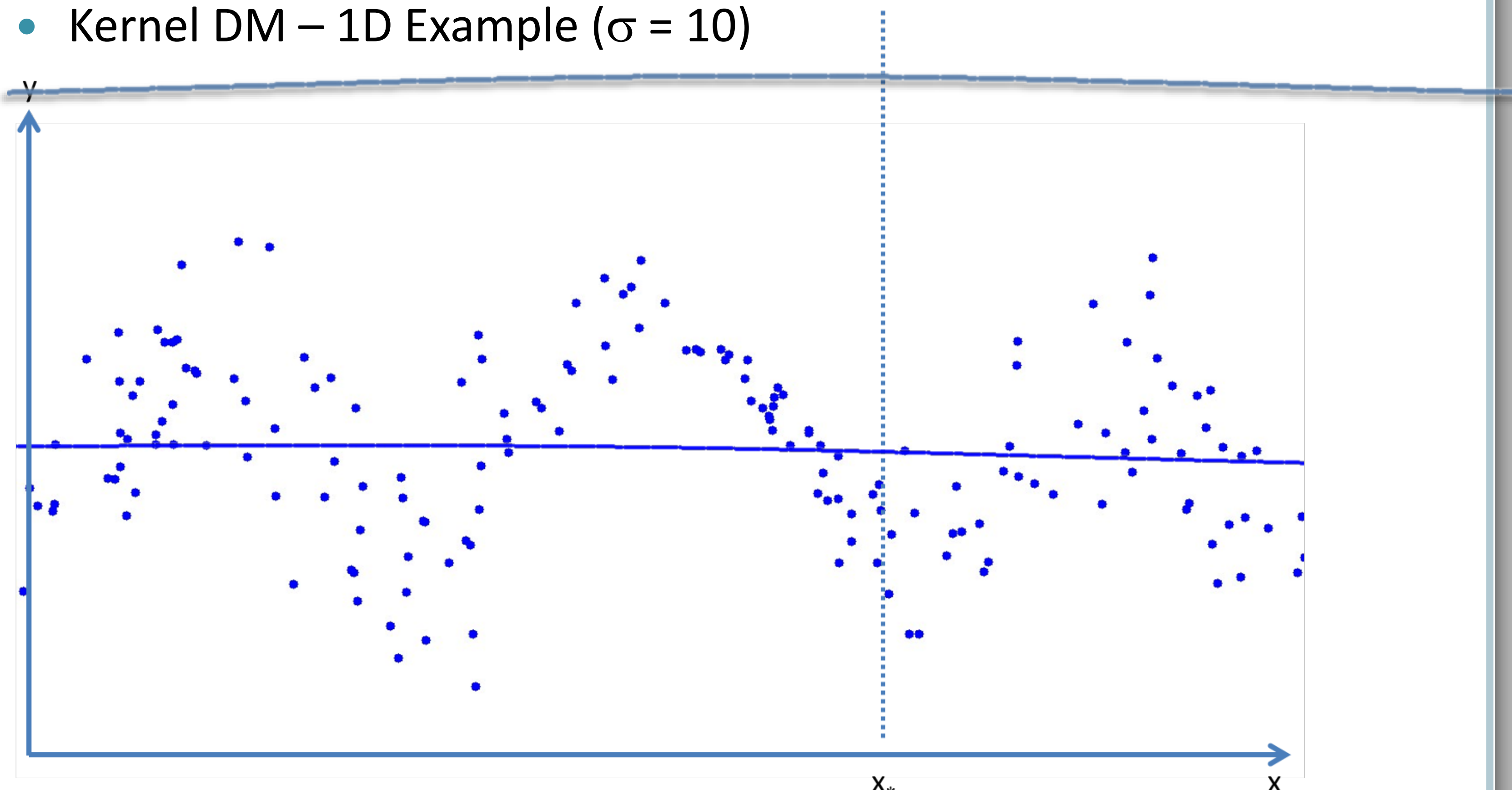
- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 2.50)



[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

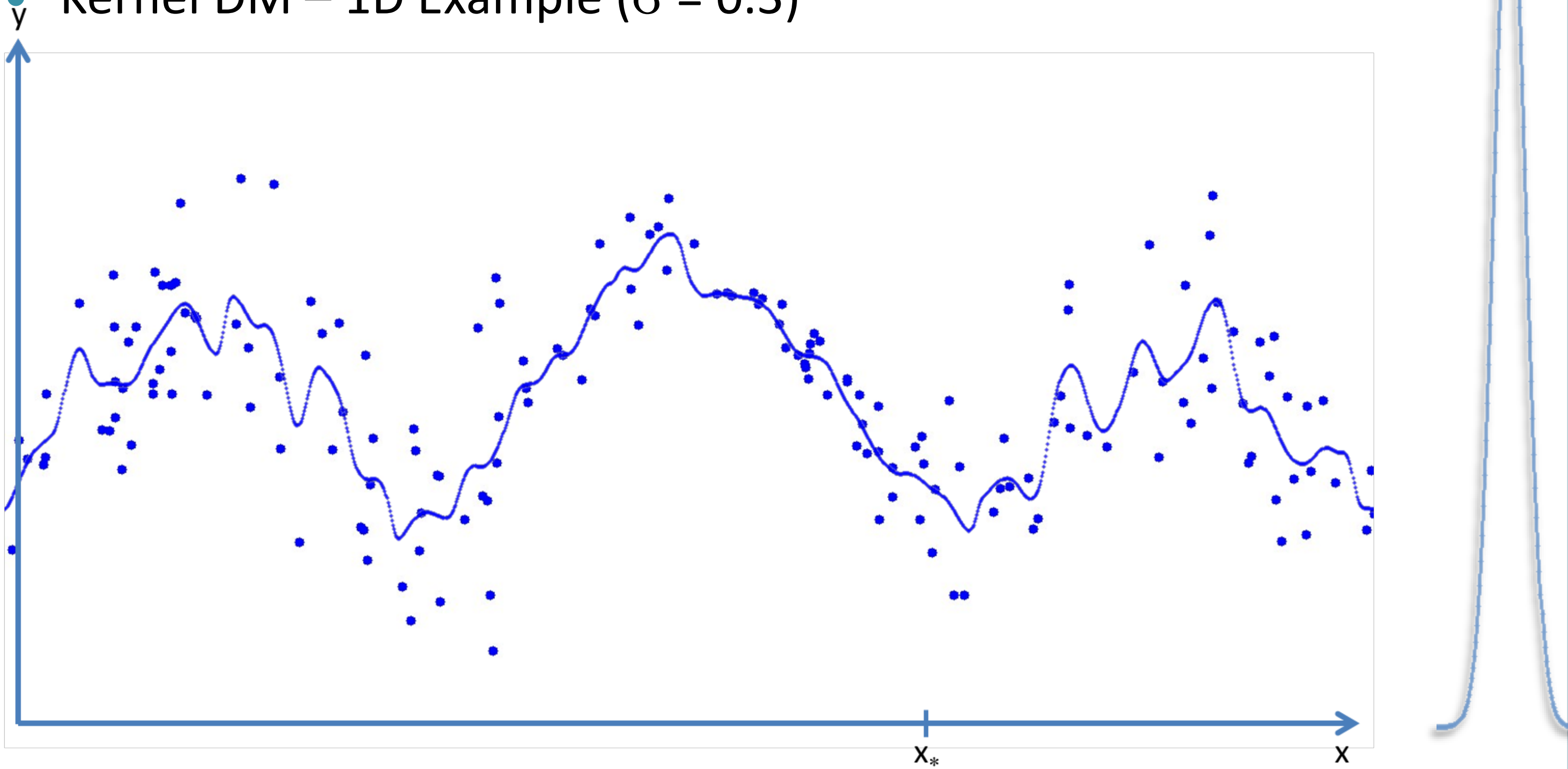
- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 10)



[Lilienthal & Duckett, RAS 2004]

Kernel DM for GDM

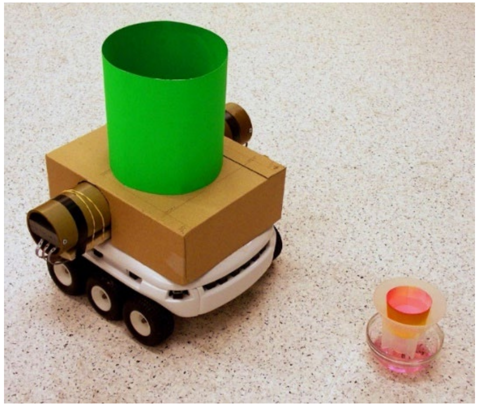
- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 0.3)

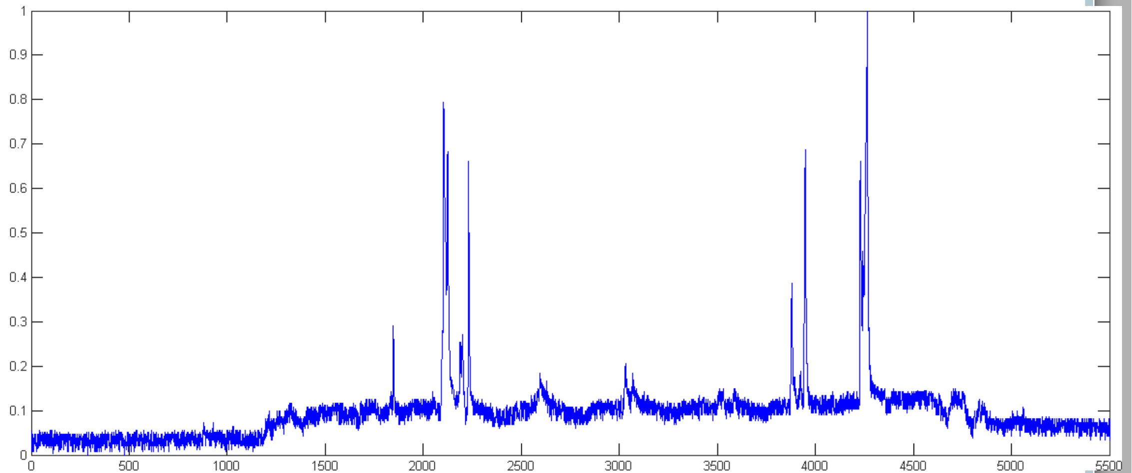


[Lilienthal & Duckett, RAS 2004]

KERNEL DM FOR GDM

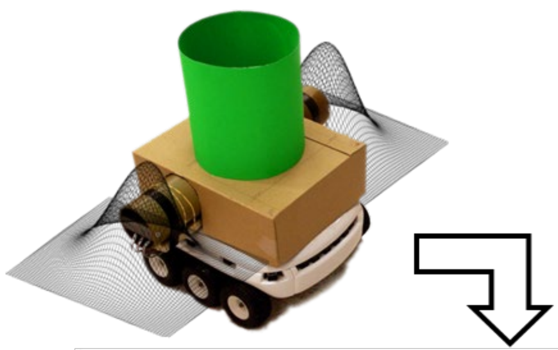
- Importance of spatial interpolation
  - Kernel DM – 2D Example (Real-World Measurements)

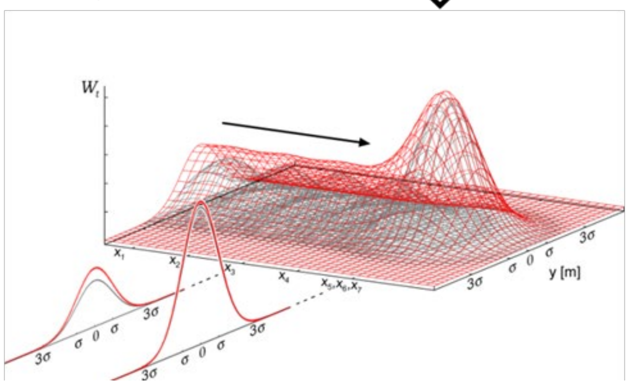


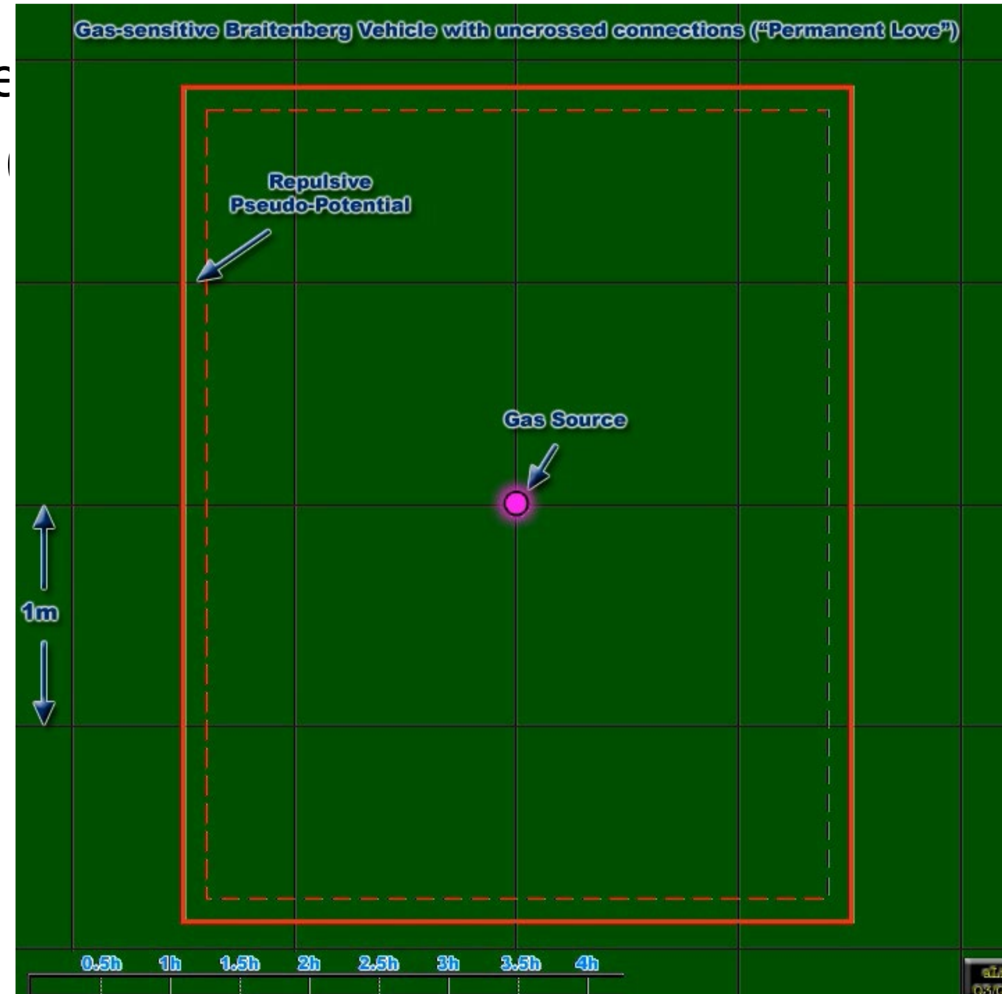


KERNEL DM FOR GDM

- Importance of spatial inte
  - Kernel DM – 2D Example (







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Early Research Work

[5] Smelling Braitenberg Vehicles

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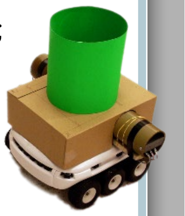
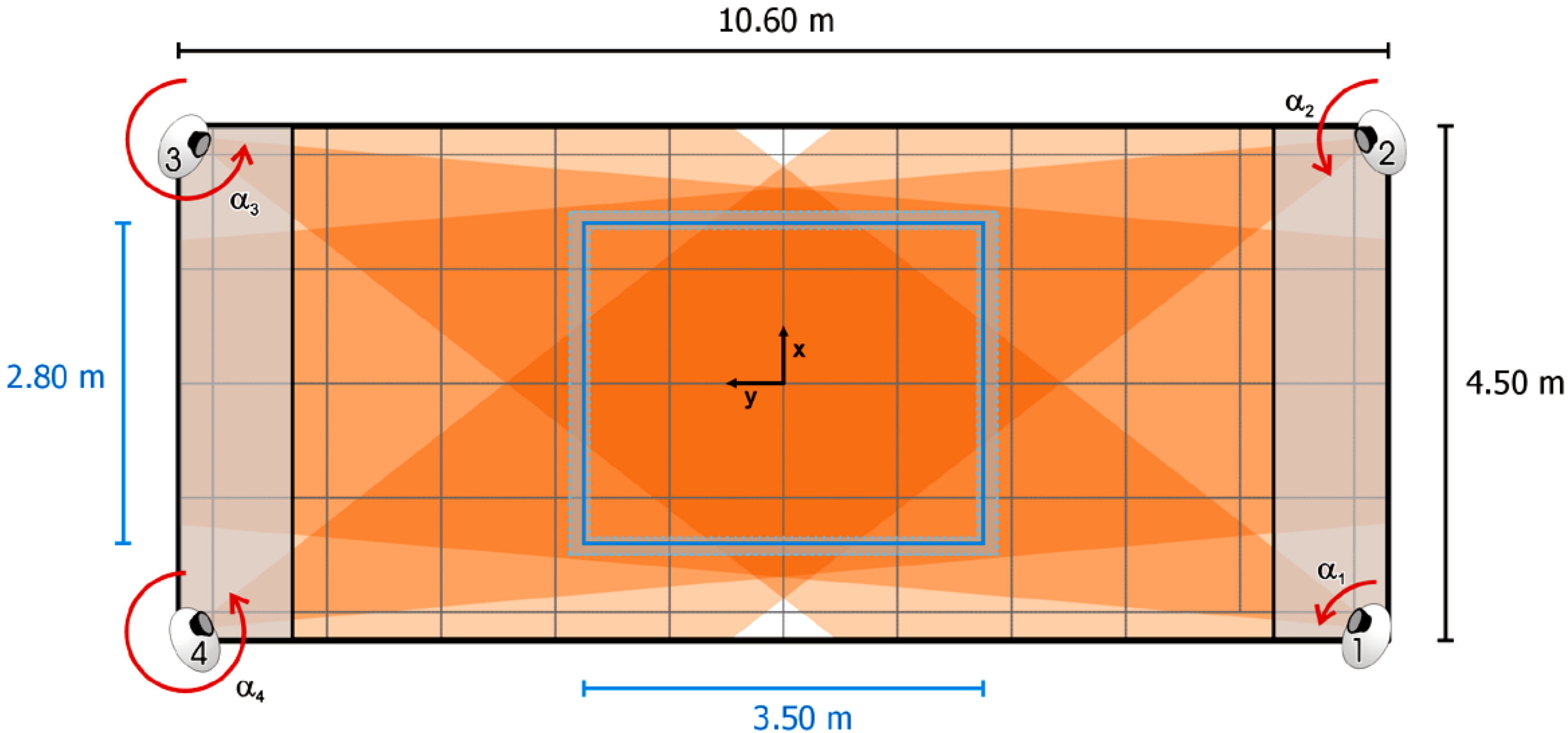
Smelling Braitenberg Vehicles

[Lilienthal and Duckett, Advanced Robotics, 2004;
Lilienthal and Duckett, ICAR, 2003]



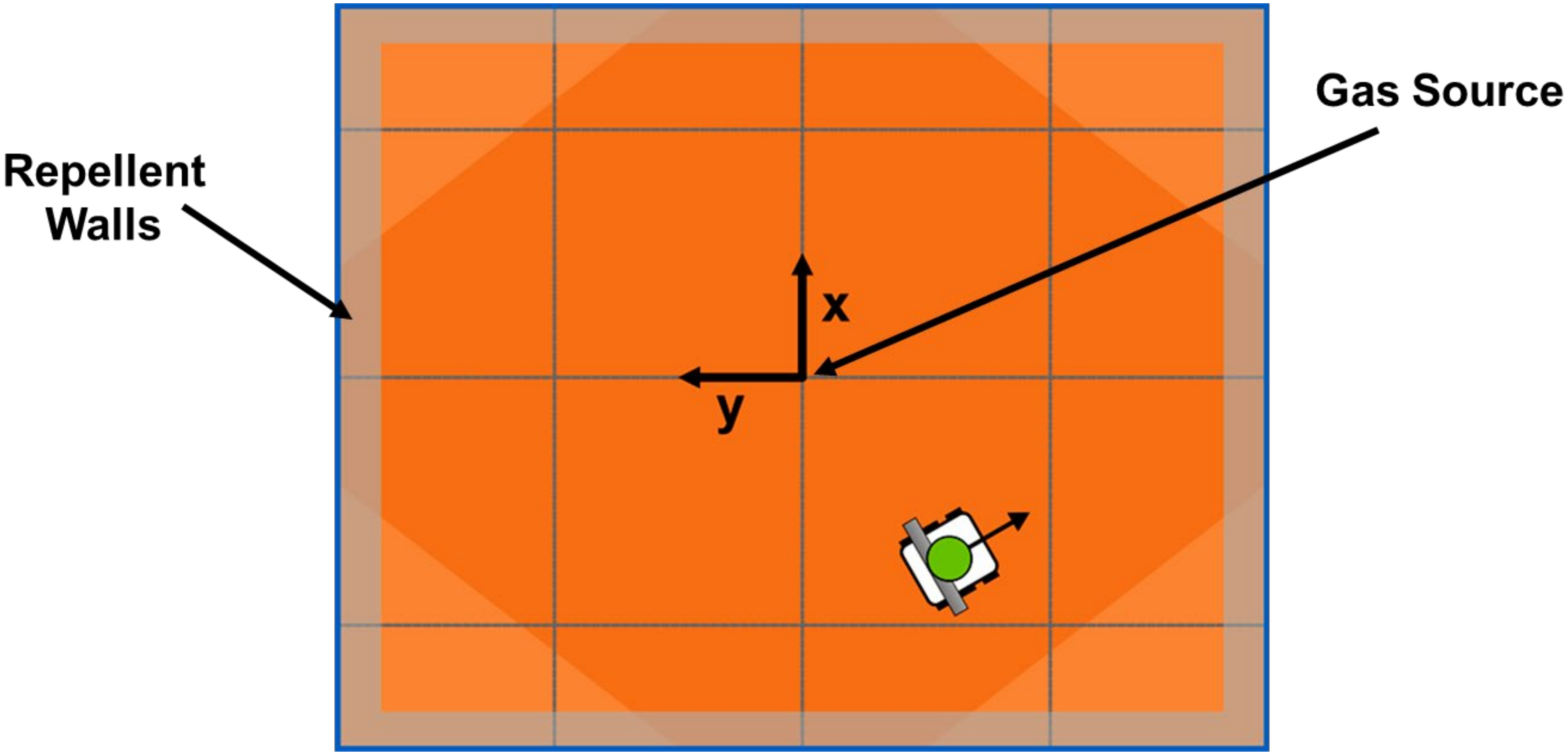
- Testbed for Gas Source Localization Strategies



SMELLING BRAITENBERG VEHICLES

[Lilienthal and Duckett, Advanced Robotics, 2004; Lilienthal and Duckett, ICAR, 2003]

- Testbed for Gas Source Localization Strategies



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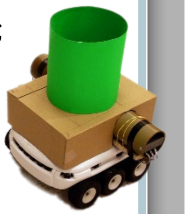
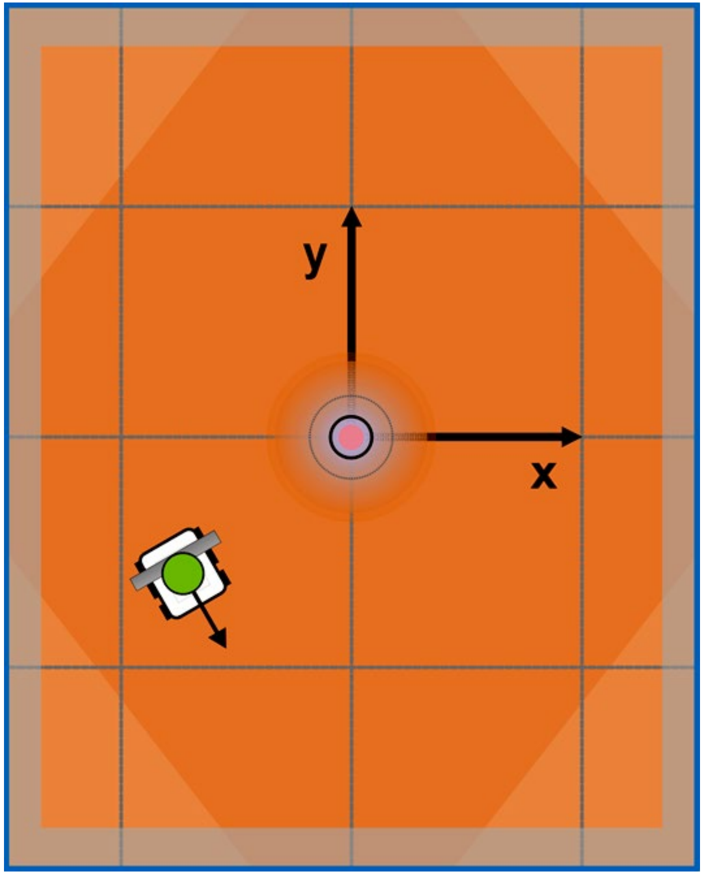
SMELLING BRAITENBERG VEHICLES

[Lilienthal and Duckett, Advanced Robotics, 2004;
Lilienthal and Duckett, ICAR, 2003]



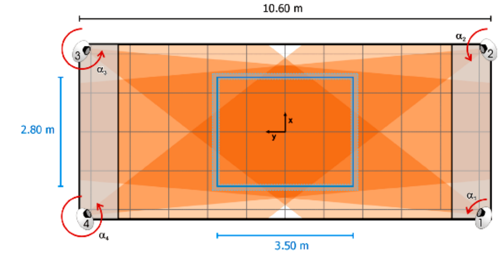
- Gas Source Localization Benchmark
  - Start
    - Random starting position
    - Min. dist. to source = 100 cm
    - Random heading
  - Source is found …
    - … if robot would "hits" it
  - Statistics
    - Path length, duration, …

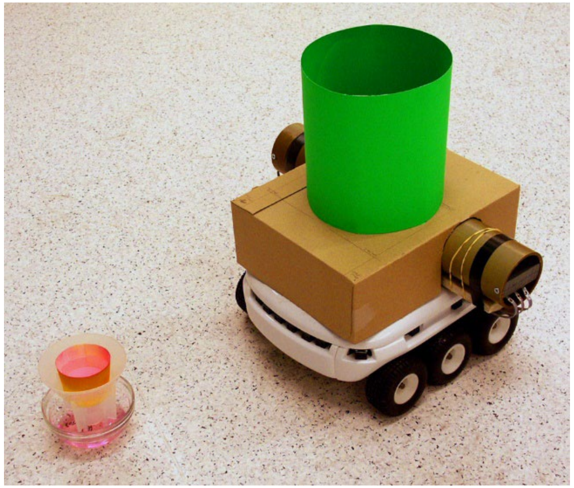


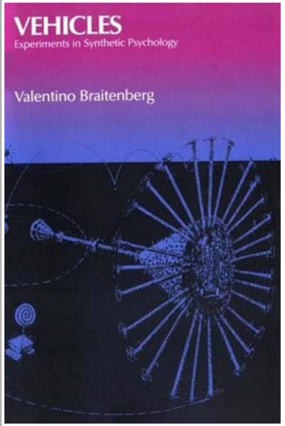
SMELLING BRAITENBERG VEHICLES

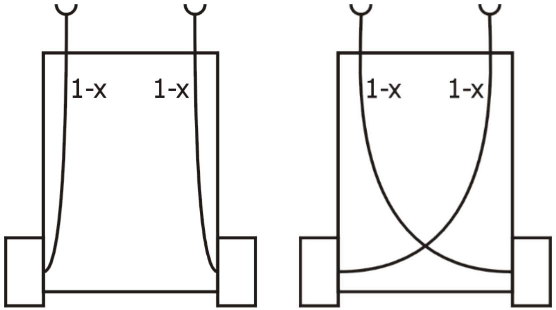
[Lilienthal and Duckett, Advanced Robotics, 2004; Lilienthal and Duckett, ICAR, 2003]

- Gas Source Localization Benchmark
  - Environment
    - No ventilation / fans
    - Indoor environment
  - Gas Source
    - Dripping liquid ethanol
  - Gas Source Tracing Strategy
    - Braitenberg vehicle



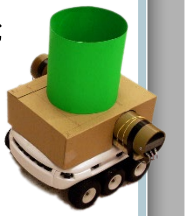




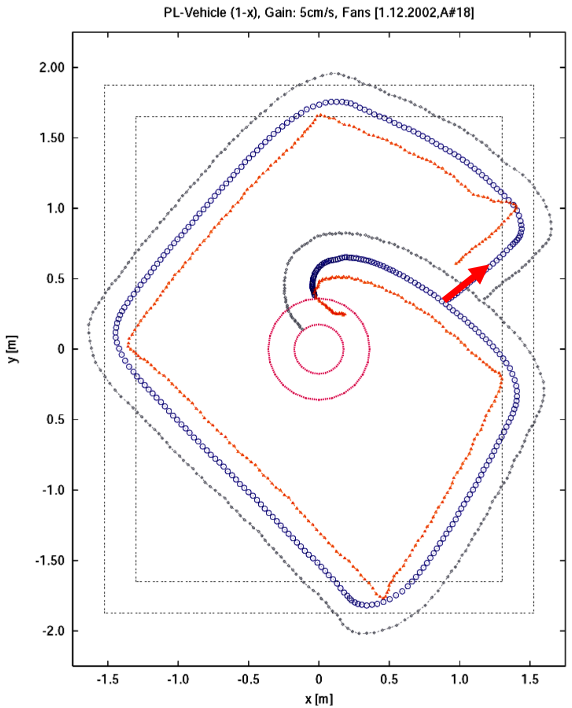


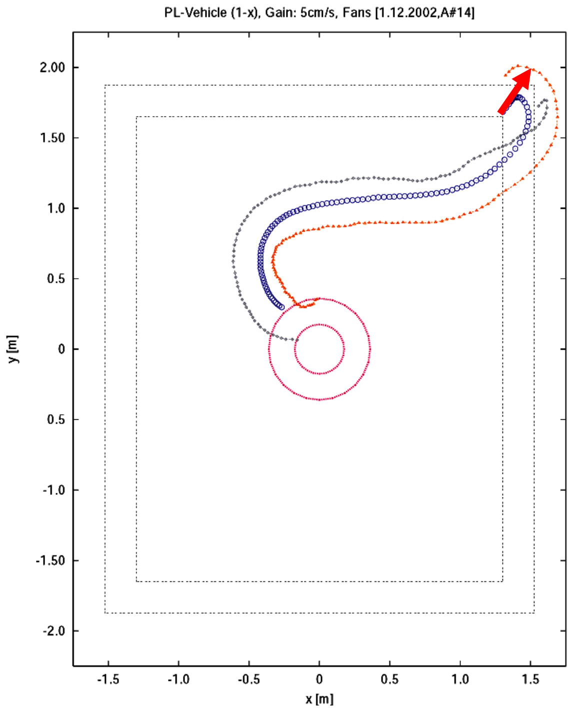
SMELLING BRAITENBERG VEHICLES

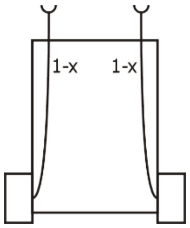
[Lilienthal and Duckett, Advanced Robotics, 2004; Lilienthal and Duckett, ICAR, 2003]



- Gas Source Tracing Braitenberg Vehicles
  - Uncrossed sensor-motor connection <= vehicle 3a ("love")
    - => Looks quite efficient sometimes ...







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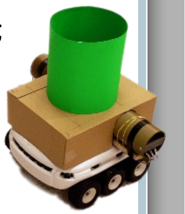
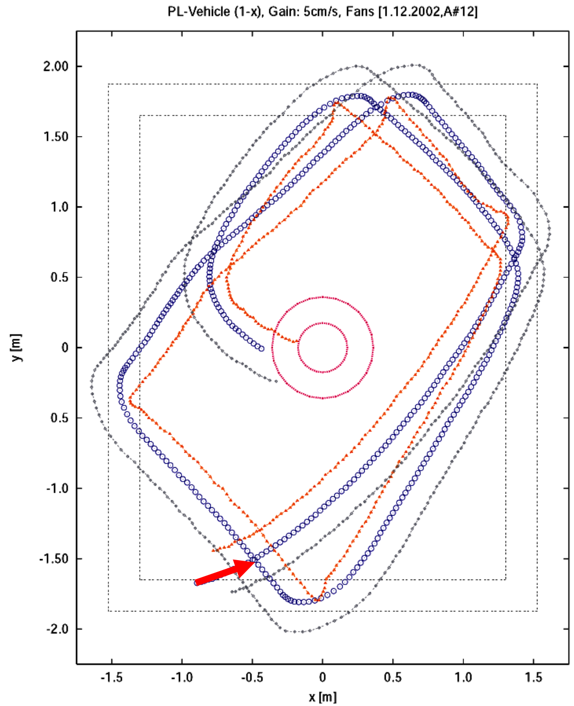
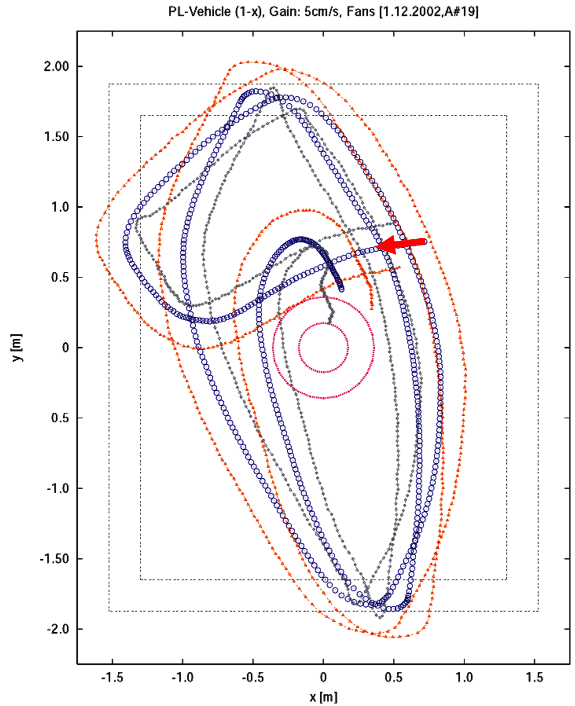
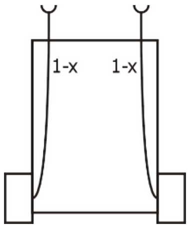


- Gas Source Tracing Braitenberg Vehicles
  - Uncrossed sensor-motor connection <= vehicle 3a ("love")
    - => ... but often the trajectories do not look efficient.







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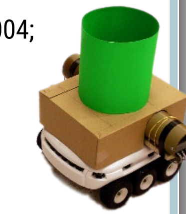
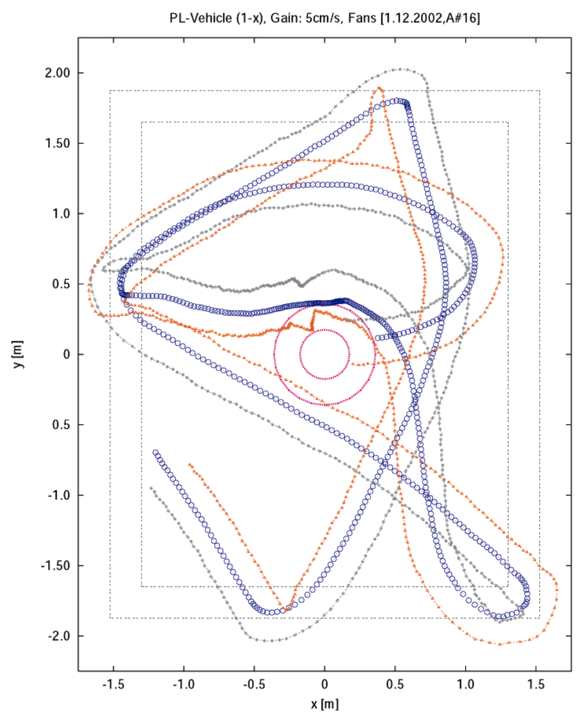
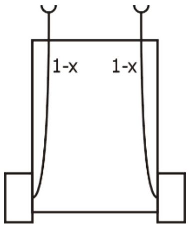


- Gas Source Tracing Braitenberg Vehicles
  - Uncrossed sensor-motor connection <= vehicle 3a ("love")
    - => ... and some trials are particularly hard to explain!





Smelling Braitenberg Vehicles

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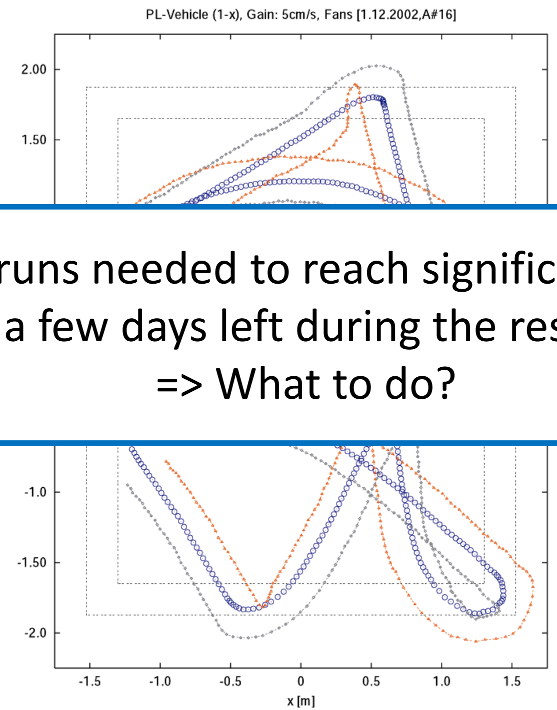

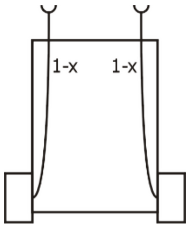

Lots of runs needed to reach significant results
BUT just a few days left during the research visit!
=> What to do?

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Smelling Braitenberg Vehicles

[Lilienthal and Duckett, Advanced Robotics, 2004;
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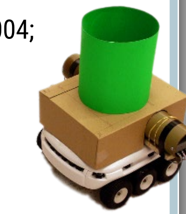
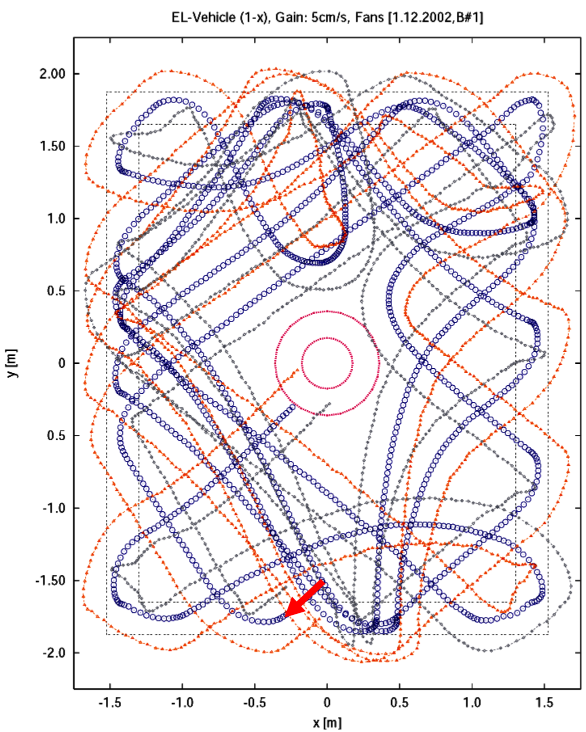
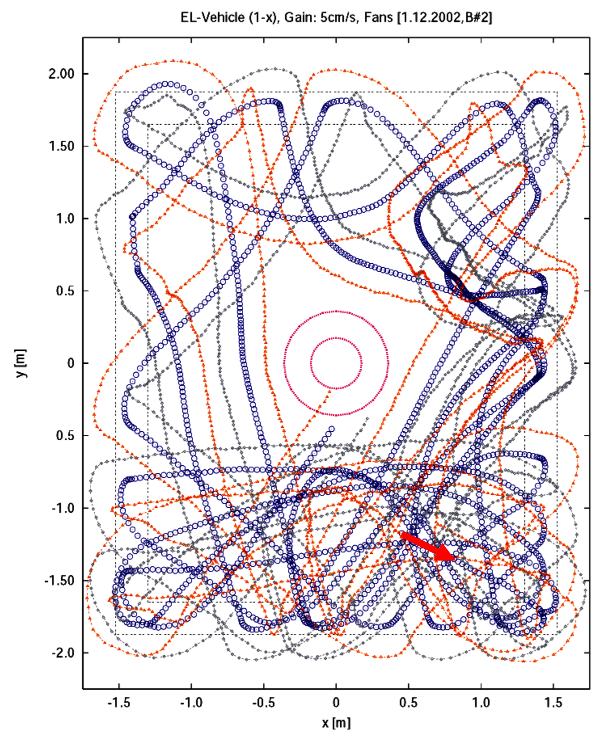
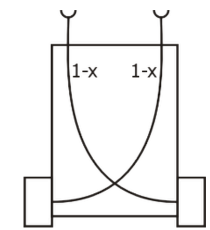


- Gas Source Tracing Braitenberg Vehicles
  - Crossed sensor-motor connection <= vehicle 3b ("explorer")
    - => Strategy turns out to be better than expected at avoiding the gas source!







SMELLING BRAITENBERG VEHICLES

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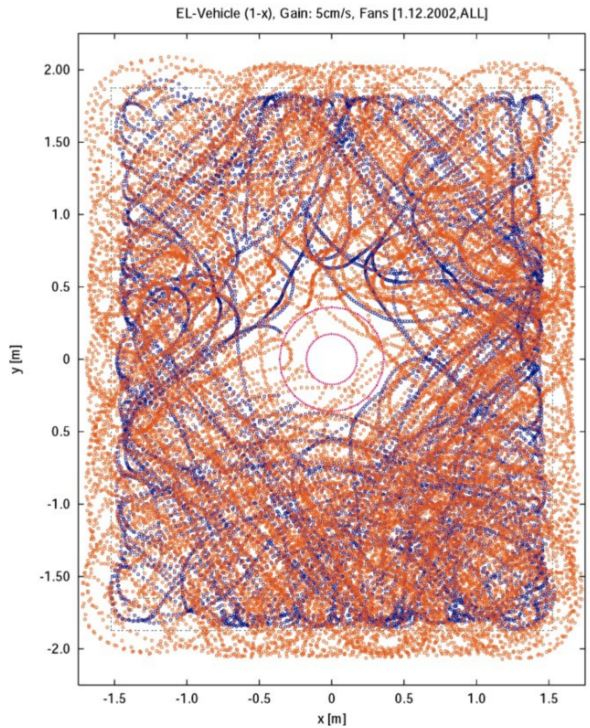

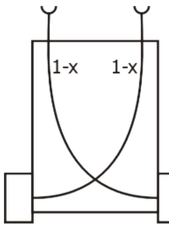

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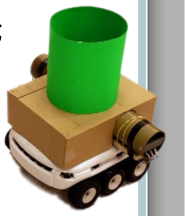
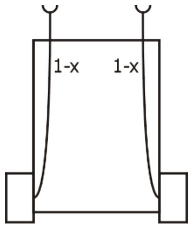
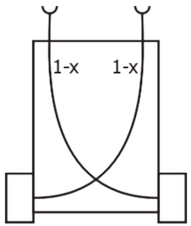


- Gas Source Tracing Braitenberg Vehicles
  - Gradient Following
    - Path length to "hit" gas source decreased
      - ≈ x0.5 compared to random search
  - Exploration + Concentration Peak Avoidance
    - Path length to "hit" gas source increased (≈ x8)
      - High concentration peak frequency seems to indicate proximity to a gas source
      - This feature may be useful for the problem of gas source declaration





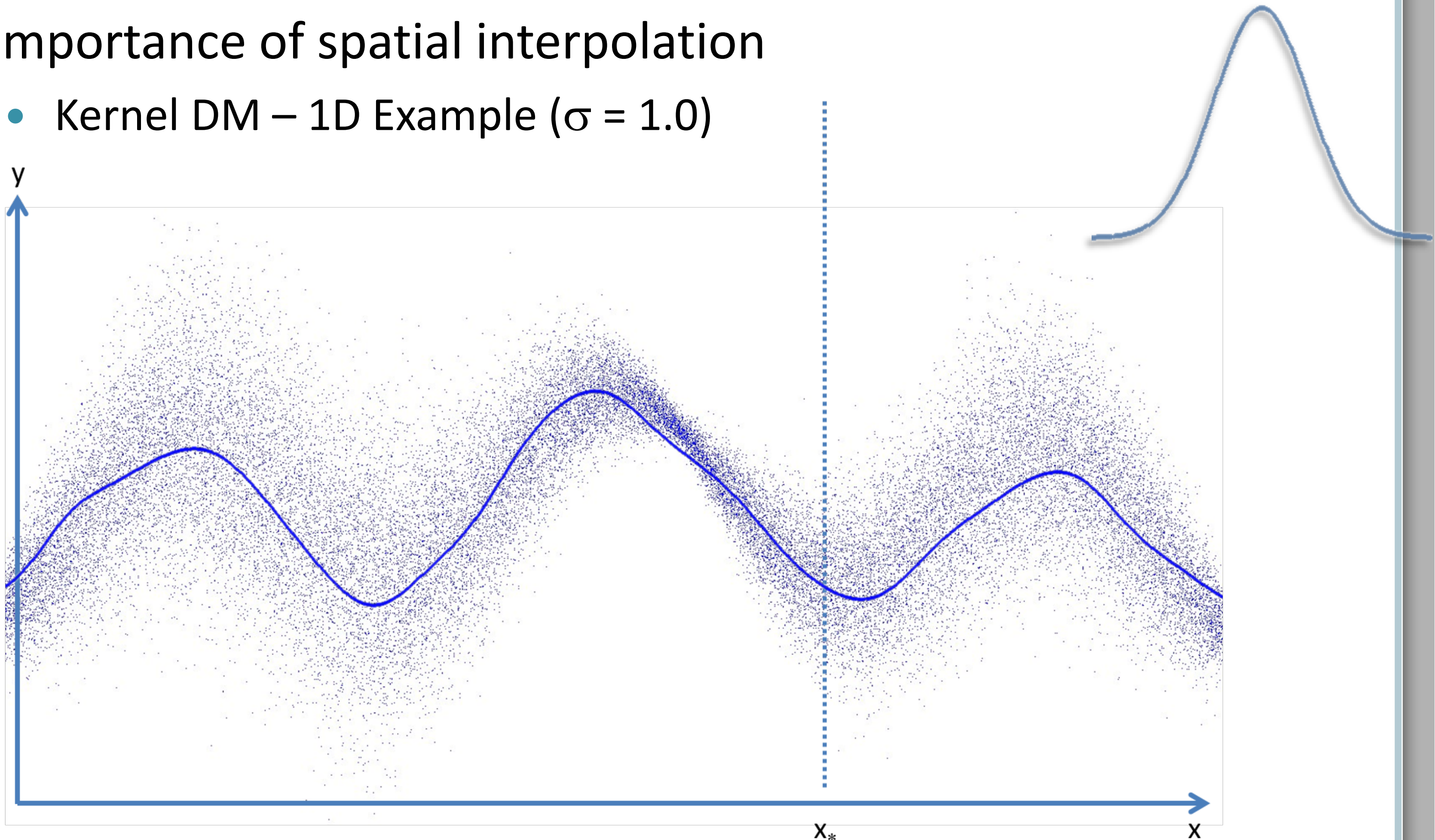
Early Research Work

[6] Kernel DM+V for GDM

[Lilienthal & Duckett, RAS 2004]

KERNEL DM+V FOR GDM

- Importance of spatial interpolation
  - Kernel DM – 1D Example (σ = 1.0)



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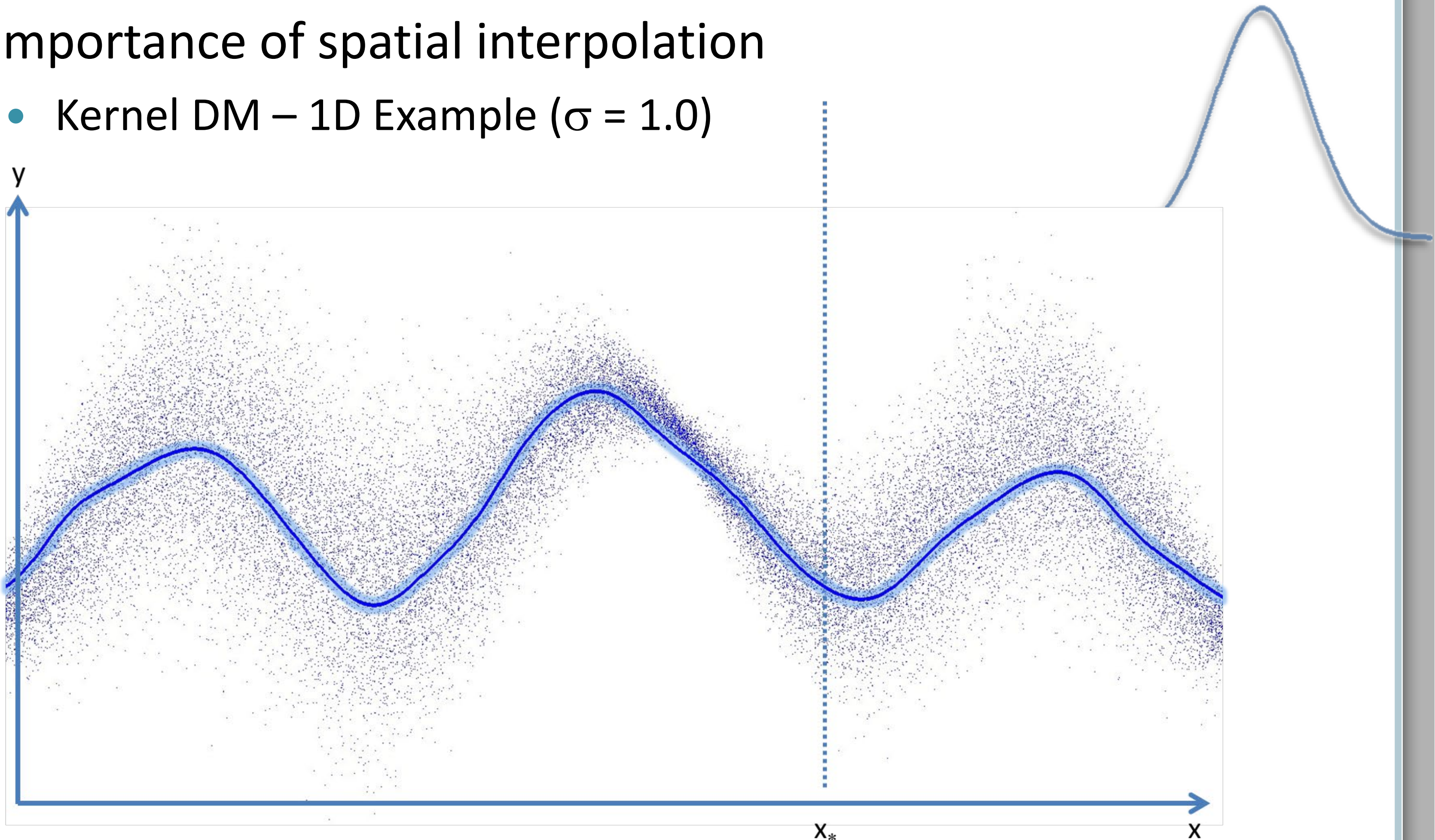

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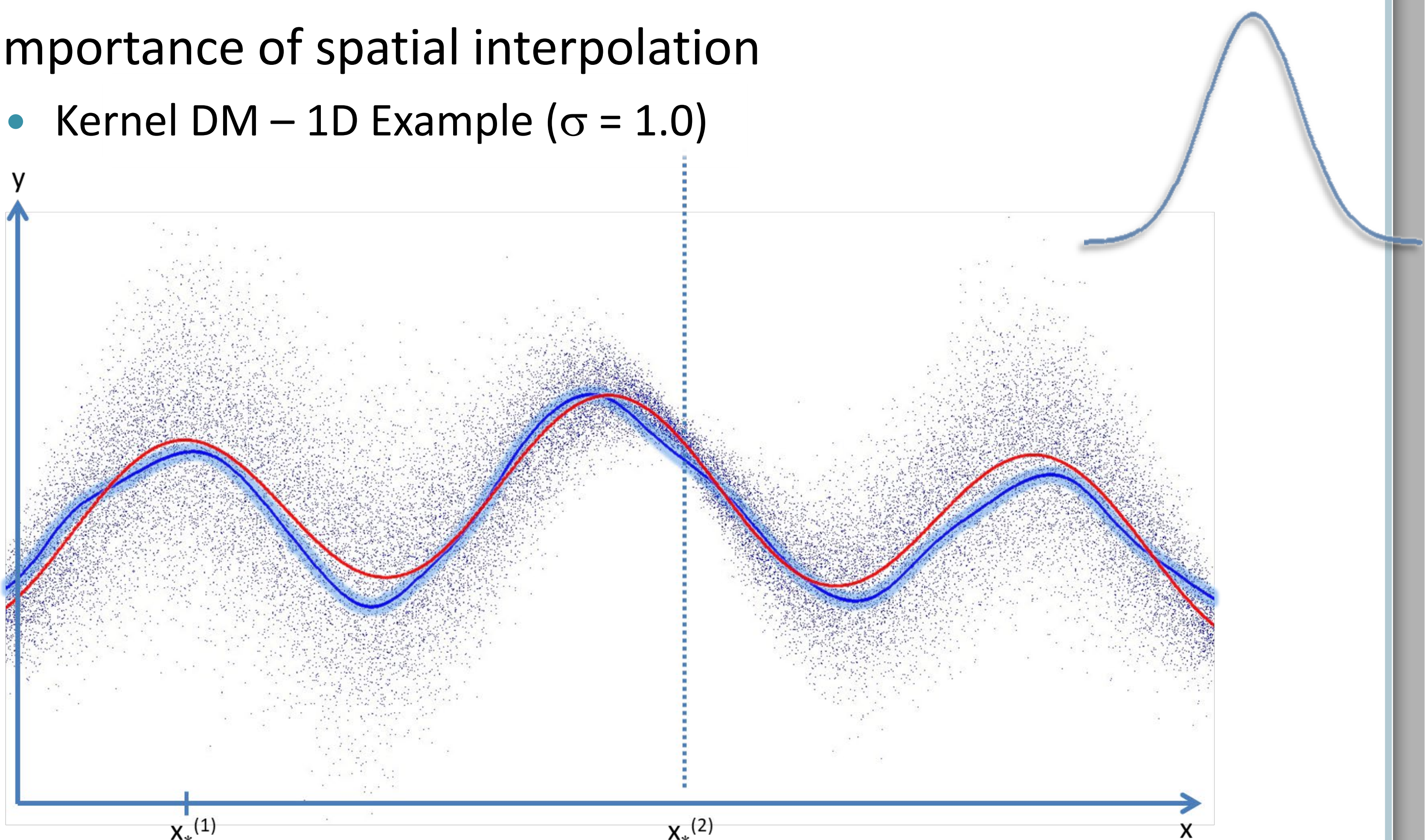

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[Lilienthal & Duckett, RAS 2004]

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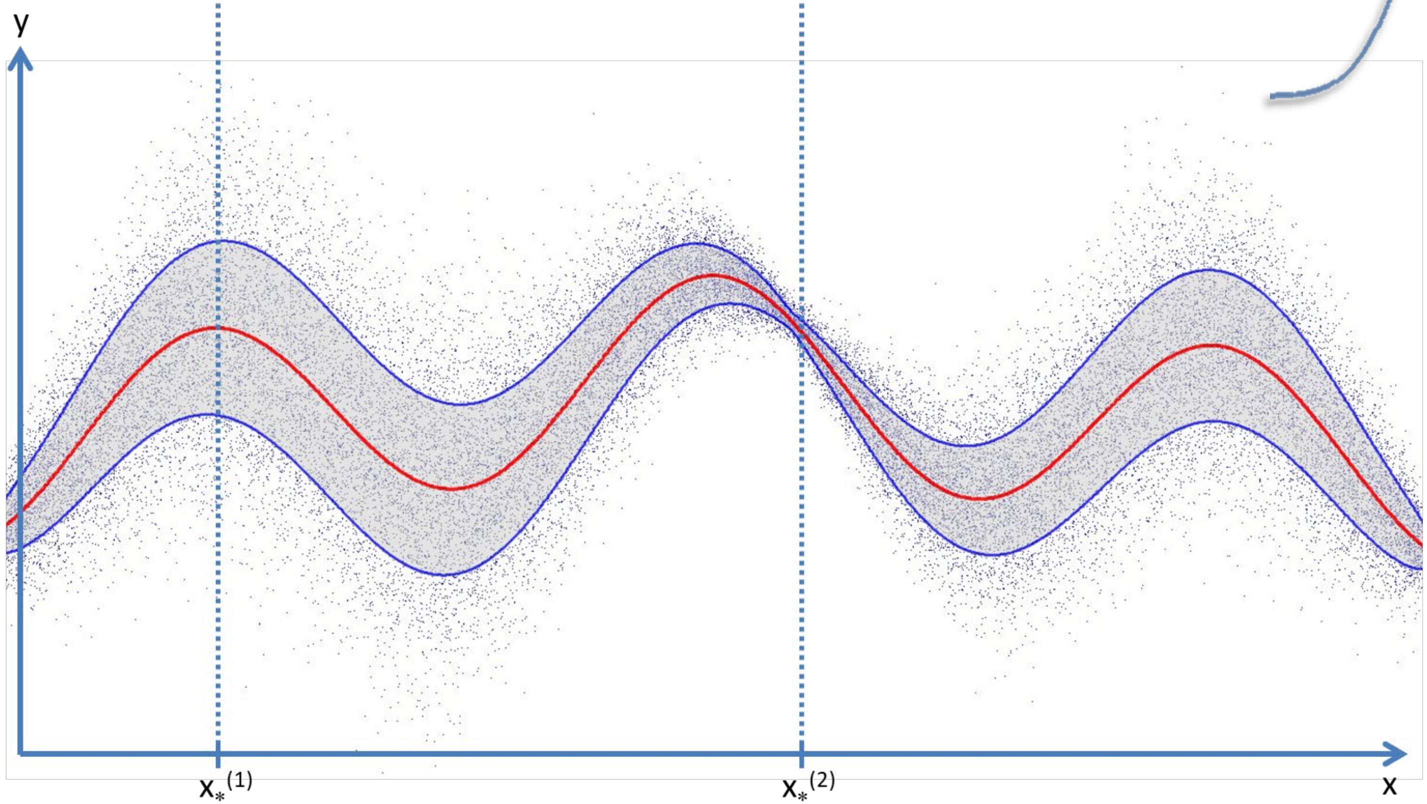
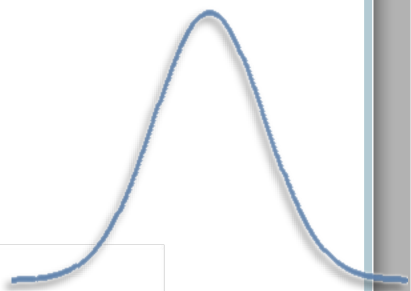
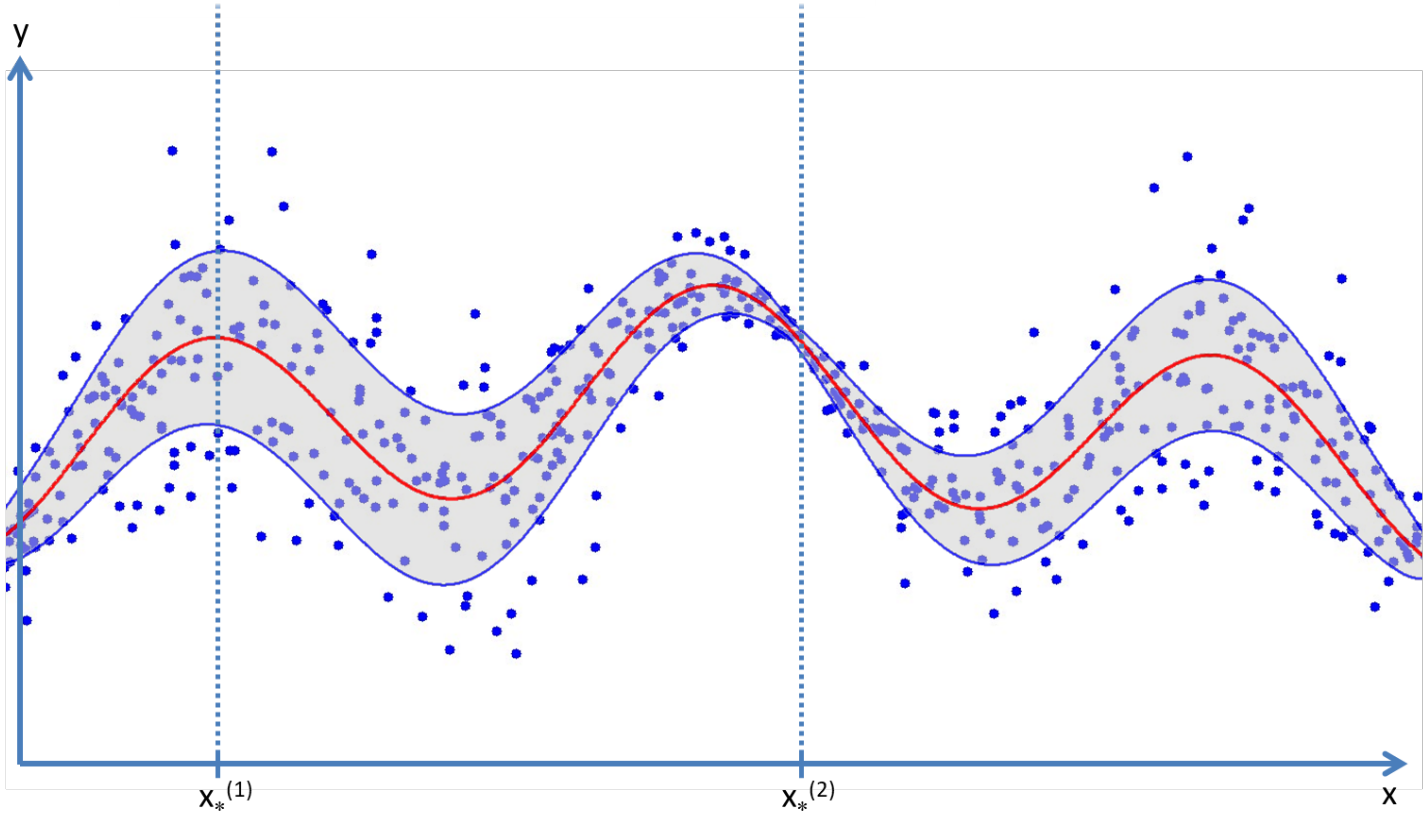




[Lilienthal et al., IROS 2009]

KERNEL DM+V FOR GDM

- Importance of spatial interpolation
  - Kernel DM+V – Two intertwined estimation processes (1D Example)



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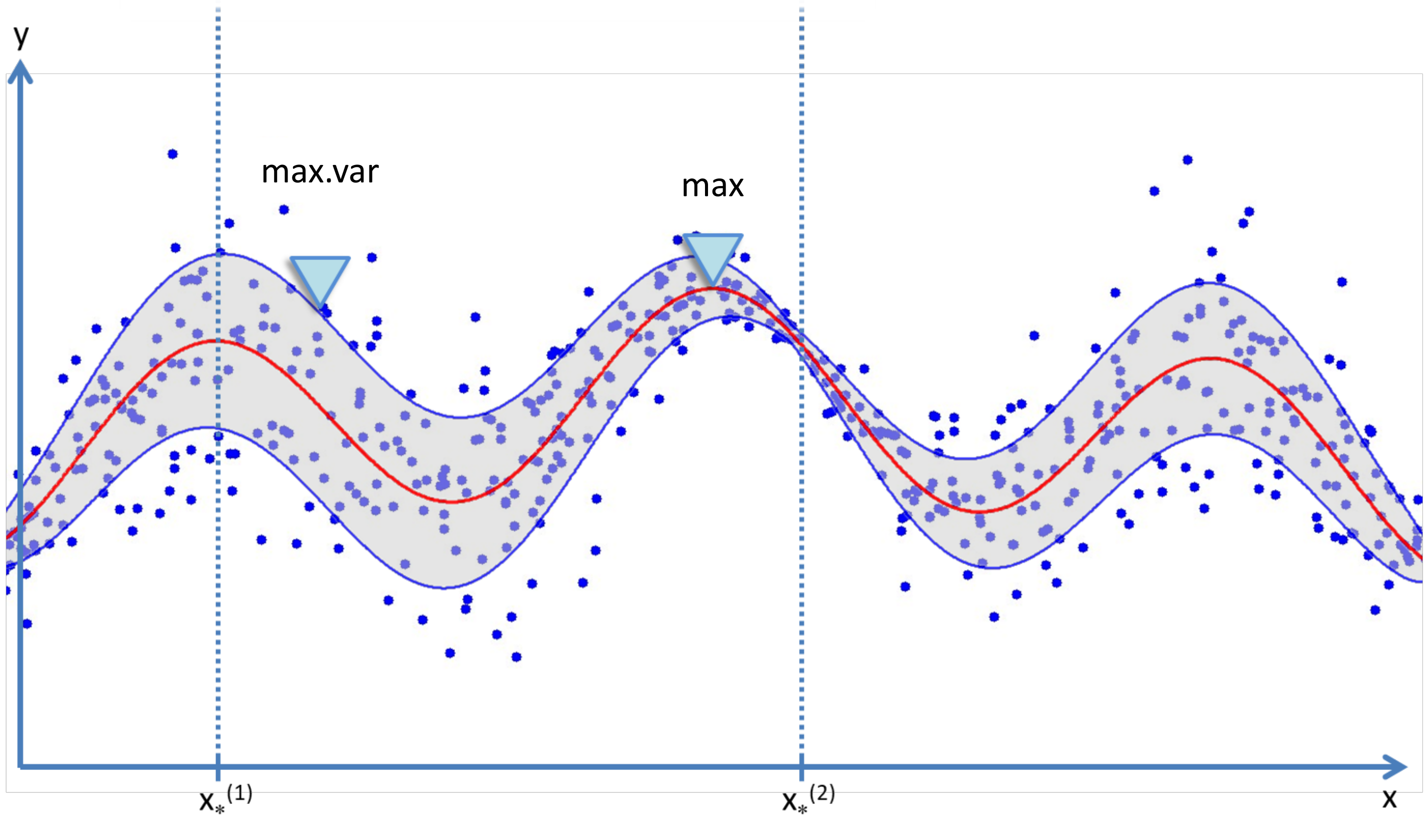

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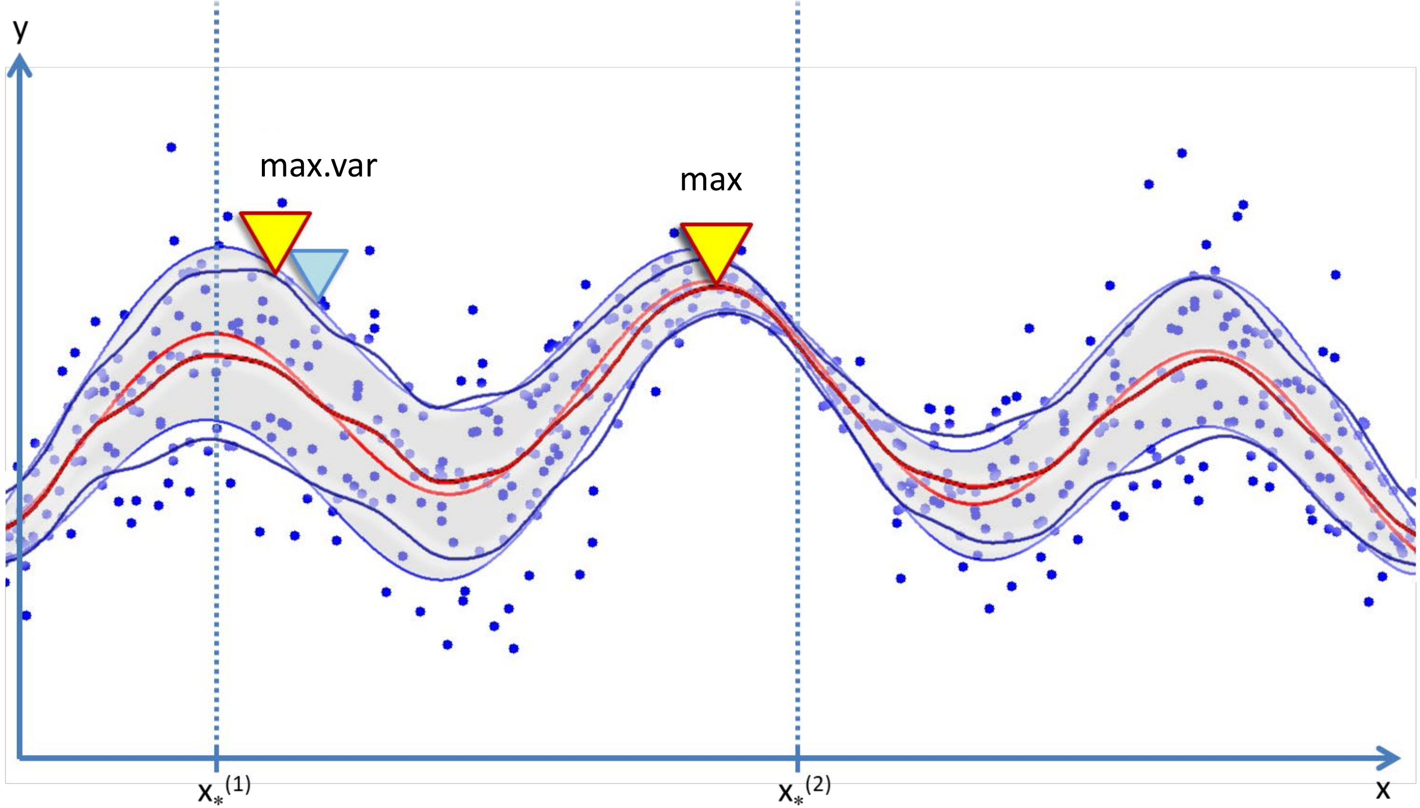

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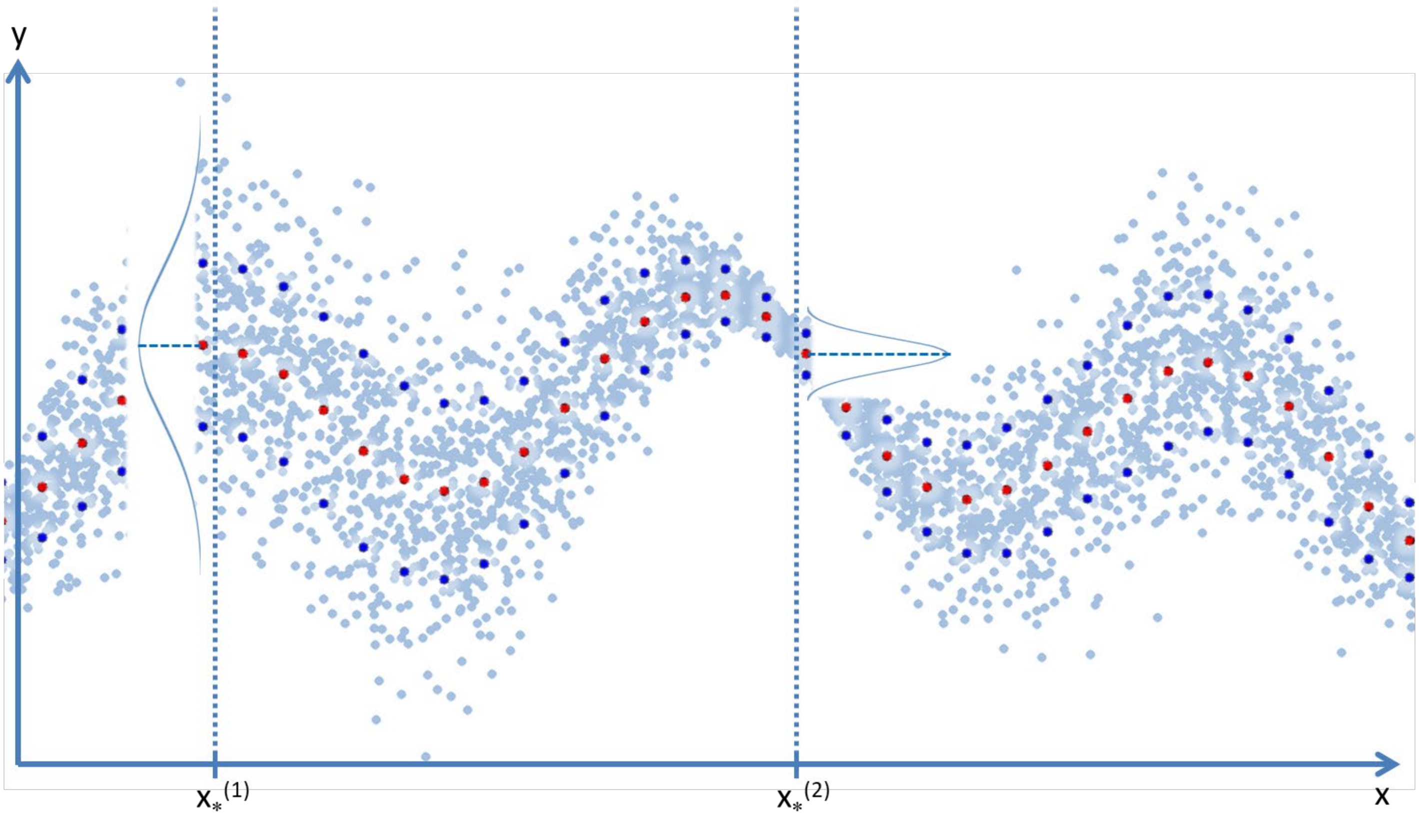
Kernel DM+V for GDM

- Importance of spatial interpolation
  - Kernel DM+V – Computed on a grid (1D Example)



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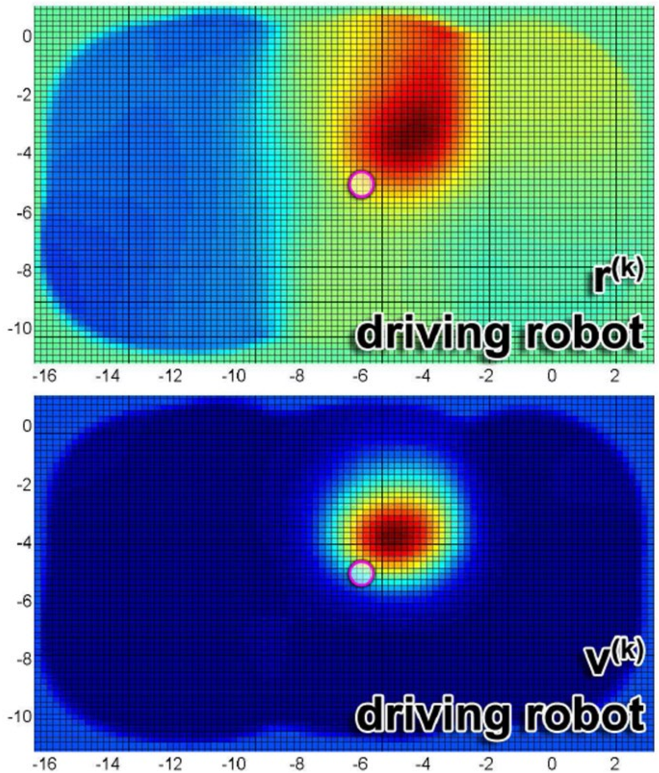

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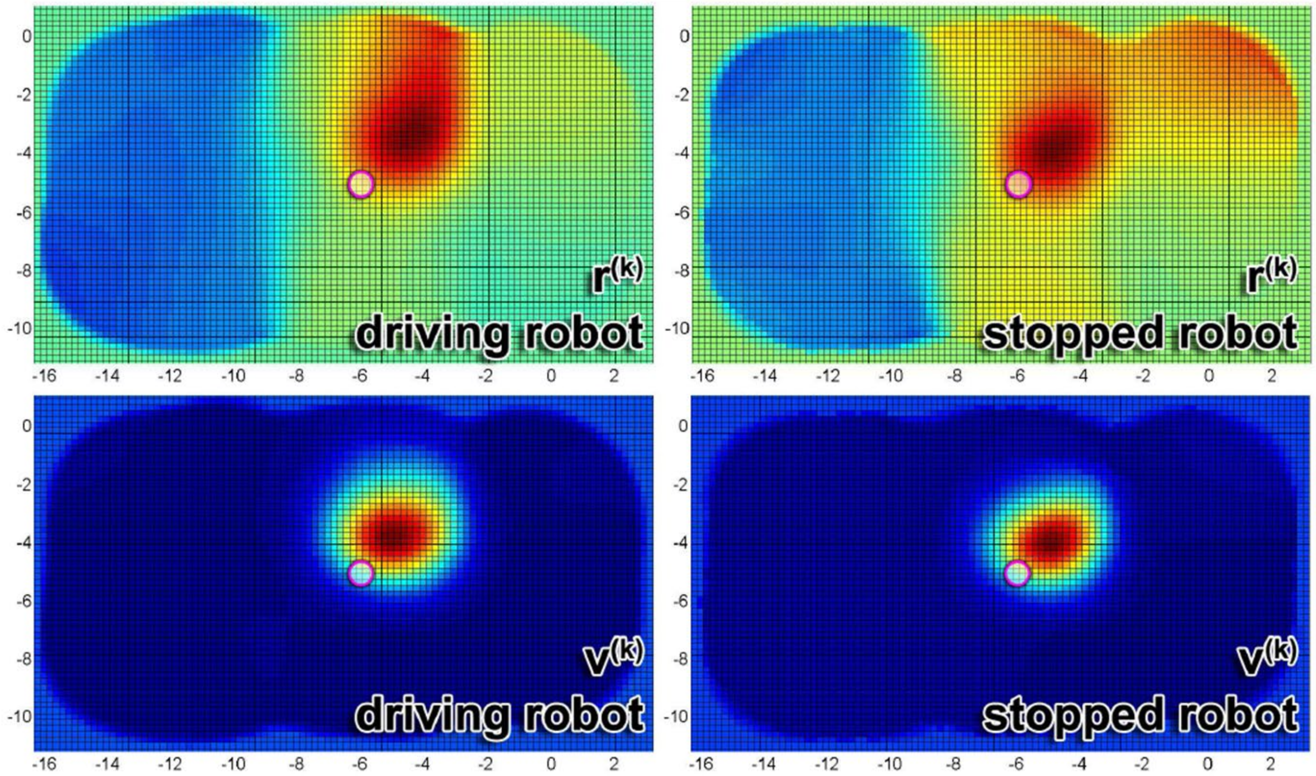


MR&O
MOBILE ROBOTICS & OLFACTION

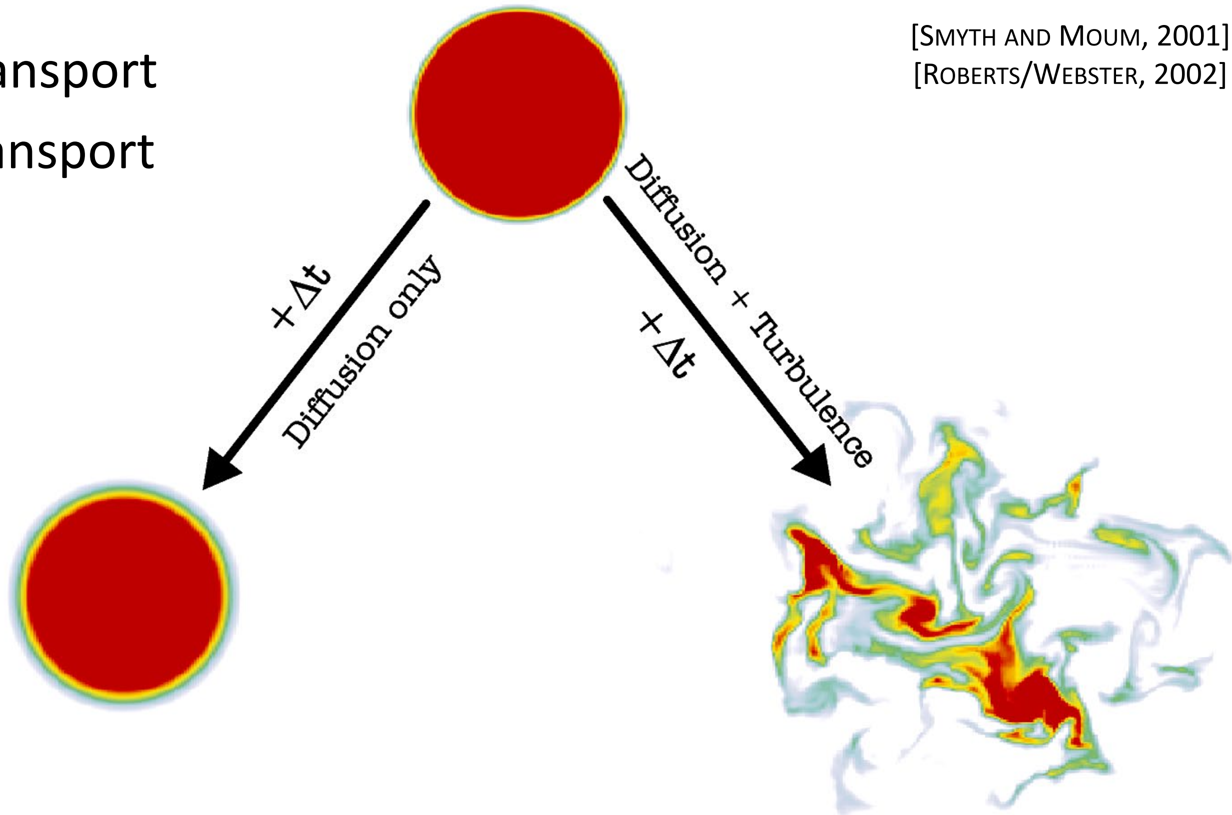
Summary & Outlook

[7] Why Mobile Robot Olfaction is Hard & How We May Address the Challenges

CHALLENGES

- Turbulent Gas Dispersal in Natural Environments
  - Diffusion
  - Advective transport
  - Turbulent transport

[SMYTH AND MOUM, 2001]
[ROBERTS/WEBSTER, 2002]



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- Turbulent Gas Dispersal in Natural Environments
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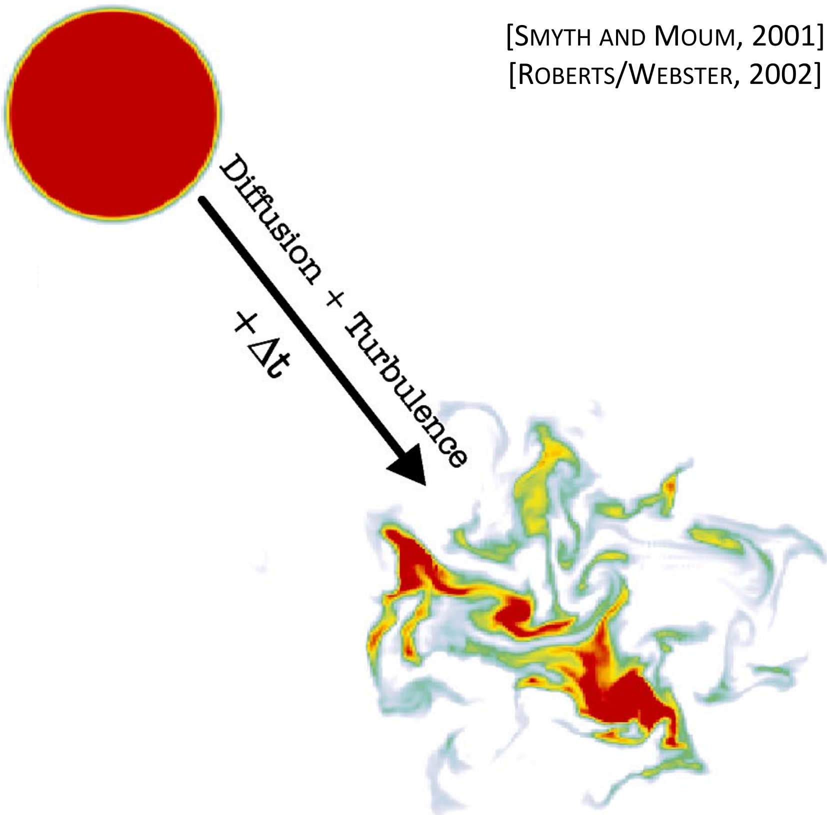

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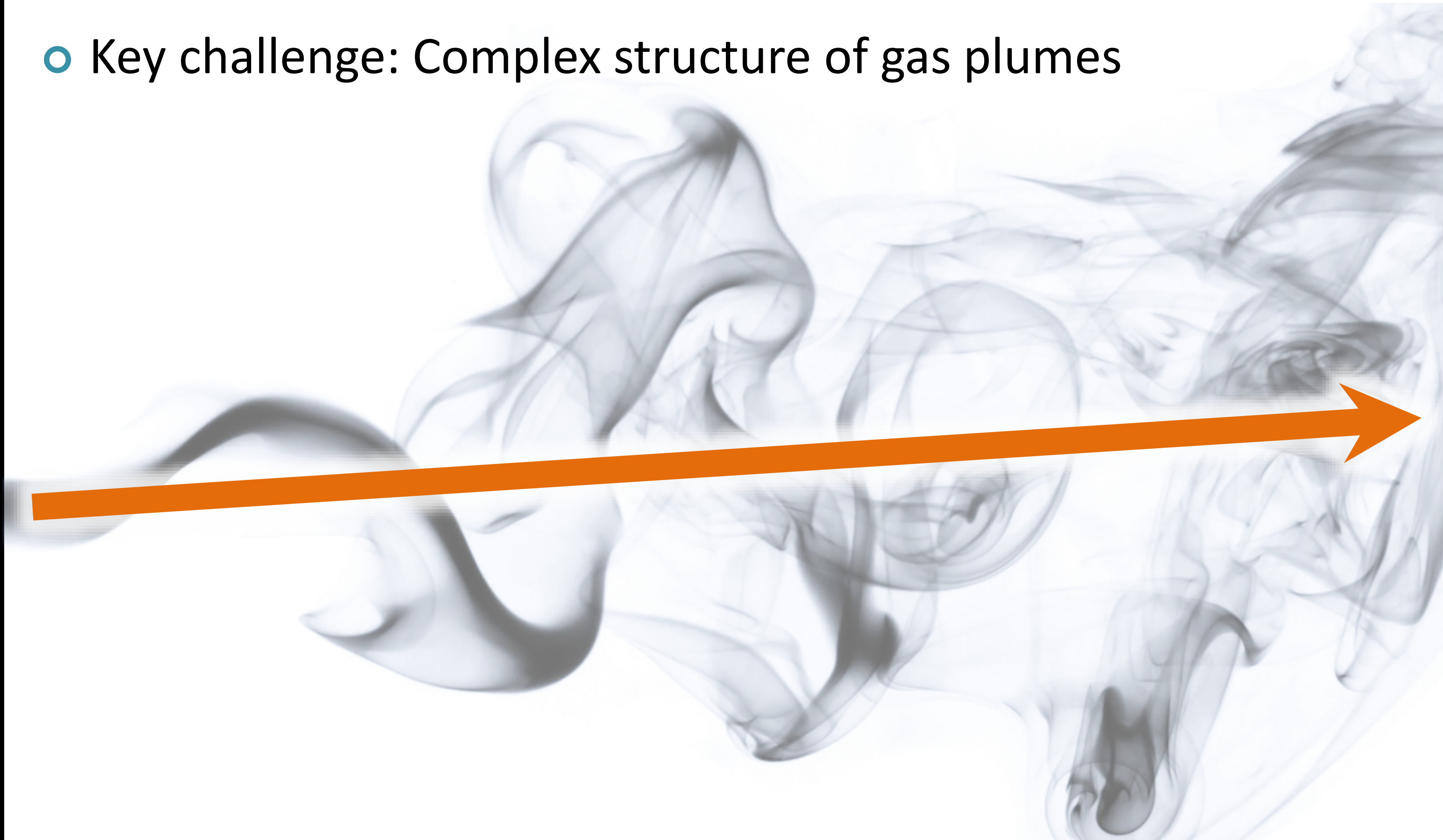
Mobile Robot Olfaction – Challenges

- Key challenge: Complex structure of gas plumes



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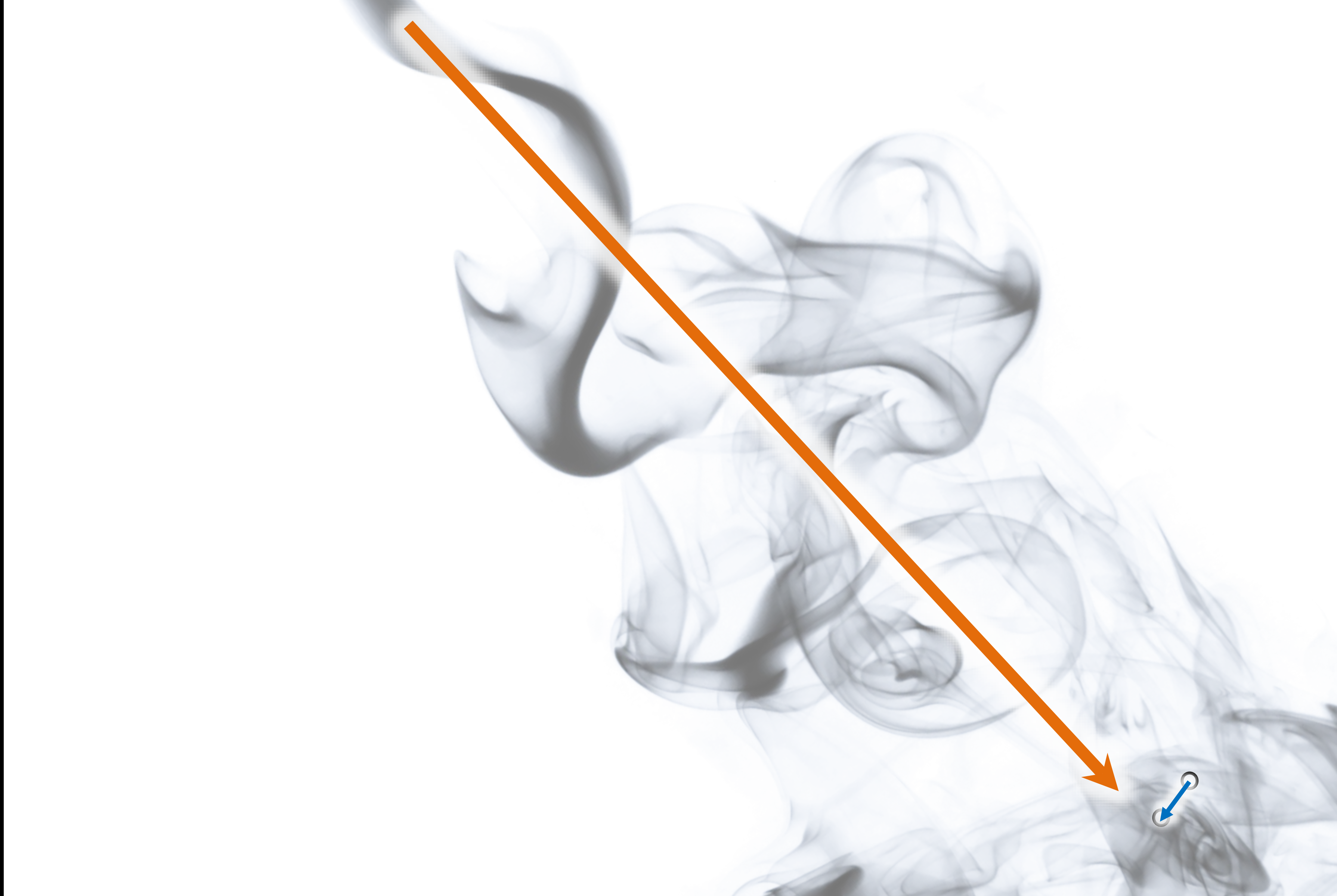

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CHALLENGES

- Turbulent Gas Dispersal in Natural Environments
- Sampling is Always Sparse!
    - => Use domain knowledge for estimation!

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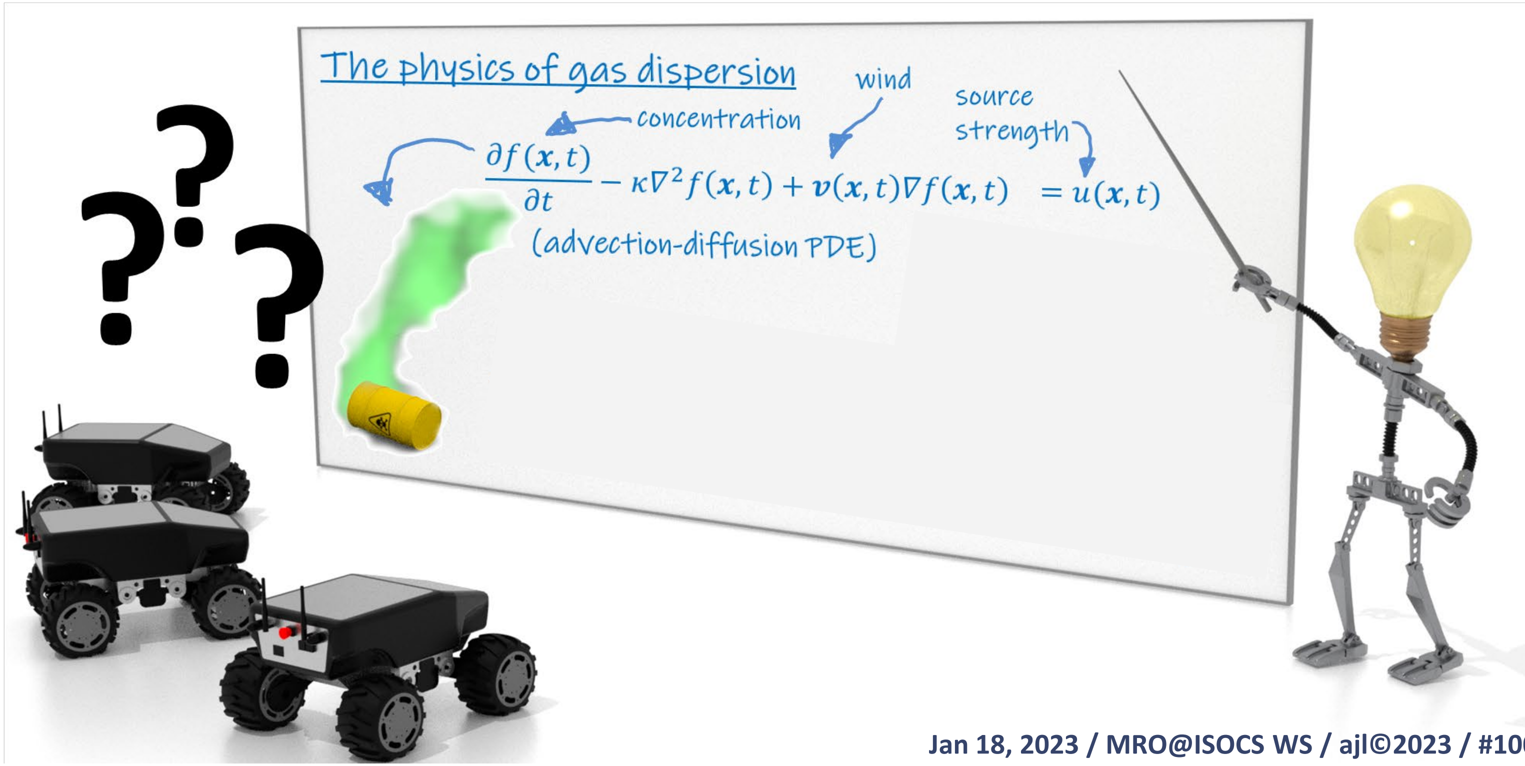
INTEGRATING PDE KNOWLEDGE FROM PHYSICS INTO GSL

[MANSS ET AL., ECMR 2015] [WIEDEMANN ET AL., ISOEN 2017]
[WIEDEMANN ET AL., SENSORS 2019] [WIEDEMANN ET AL., RAS 2019]

- Motivation
  - Hypothesis: Making PDE Domain Knowledge about gas dispersion available to AI reasoning helps in MRO tasks ("Beyond Blind AI")



Integrating PDE Knowledge From Physics Into GSL

[Manss et al., ECMR 2015] [Wiedemann et al., ISOEN 2017] [Wiedemann et al., Sensors 2019] [Wiedemann et al., RAS 2019]

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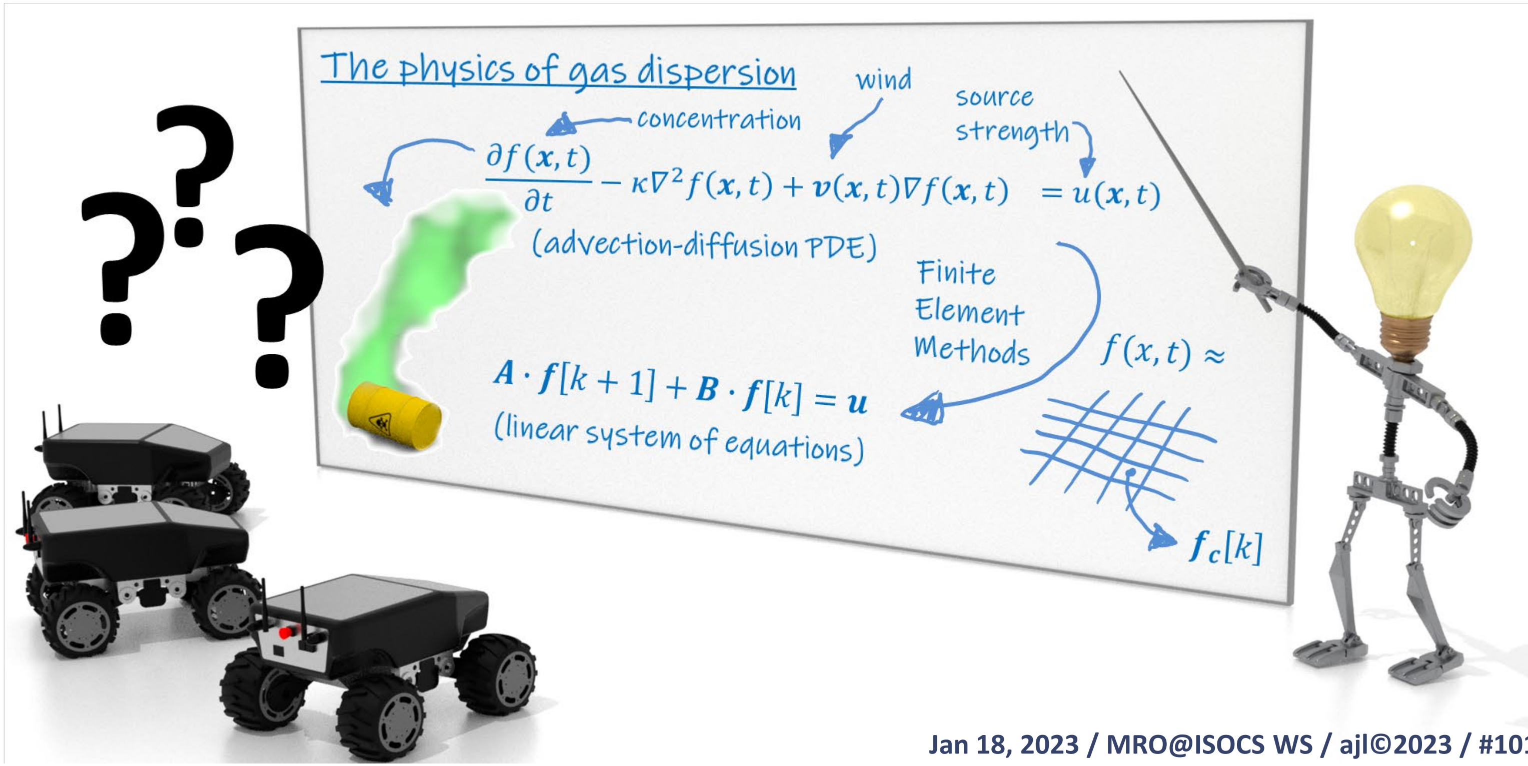

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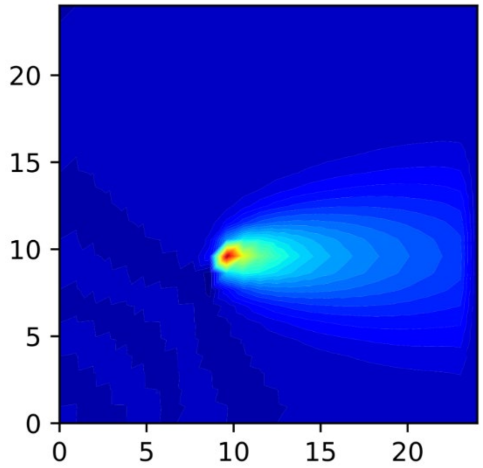
[WIEDEMANN ET AL., SENSORS 2019] [WIEDEMANN ET AL., RAS 2019]

- Motivation
  - Hypothesis: Making PDE Domain Knowledge about gas dispersion available to AI reasoning helps in MRO tasks ("Beyond Blind AI")
  - Motivation for a probabilistic approach?
    - => Handling incorrect model assumptions or incomplete knowledge

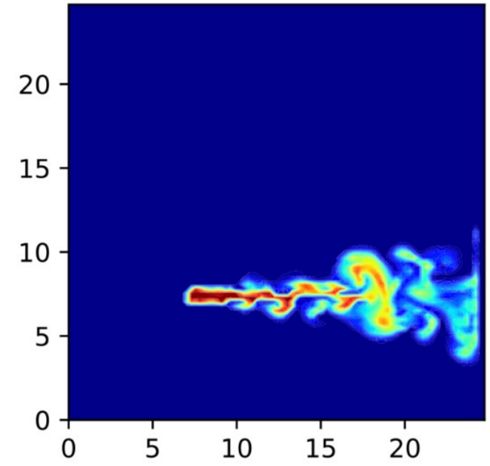
PDE approximation



model mismatch

≠

real world



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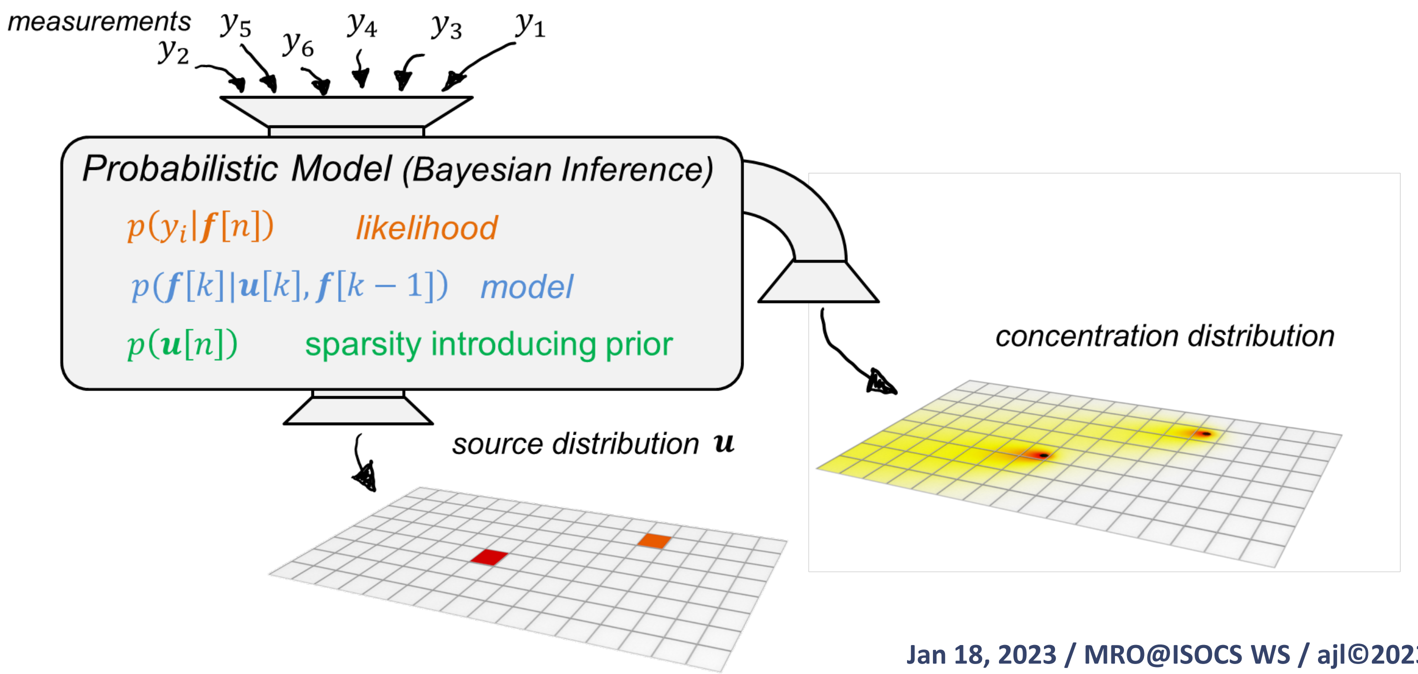
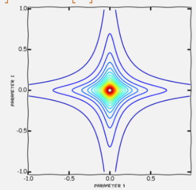


Measurement Model: $y_f[n] = \boldsymbol{M}_f\, \boldsymbol{f}[n] + \varepsilon_f \quad \longrightarrow \quad p(y_f|\boldsymbol{f}[n]) \propto e^{-\tau_f (y_f - \boldsymbol{M}_f\, \boldsymbol{f}[n])^2}$

Relaxed PDE Model: $\boldsymbol{f}[n] - \boldsymbol{f}[n-1] - \kappa \boldsymbol{D}\cdot \boldsymbol{f}[n] + \boldsymbol{v}_{x1}[n] \circ \boldsymbol{G}_{x1}\cdot \boldsymbol{f}[n] + \boldsymbol{v}_{x2}[n] \circ \boldsymbol{G}_{x2}\cdot \boldsymbol{f}[n] - \boldsymbol{B}\cdot \boldsymbol{u}[n] = \boldsymbol{r}$

residual $r=0$ with certain precision

$\longrightarrow \quad p(\boldsymbol{f}[n]|\boldsymbol{v}_1[n], \boldsymbol{v}_2[n], \boldsymbol{u}[n], \boldsymbol{f}[n-1]) \propto e^{-\tau_s \boldsymbol{r}^T \boldsymbol{r}}$

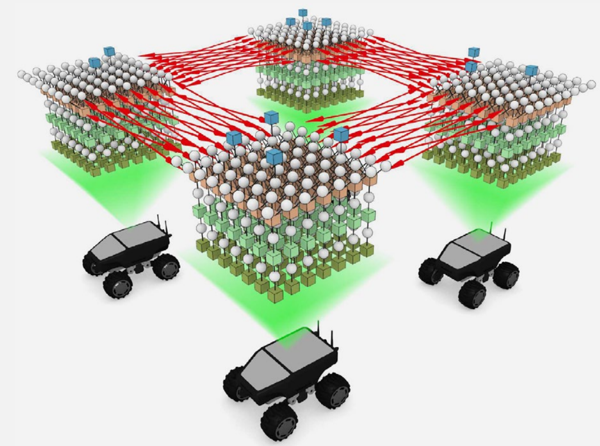


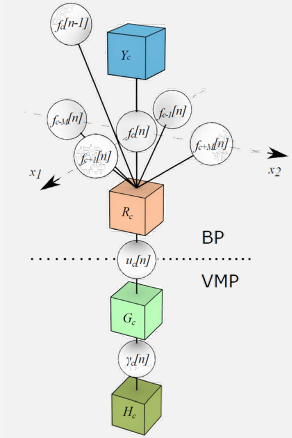
Sparsity Assumption: Regularization $\min \#\{u_i \neq 0\}$

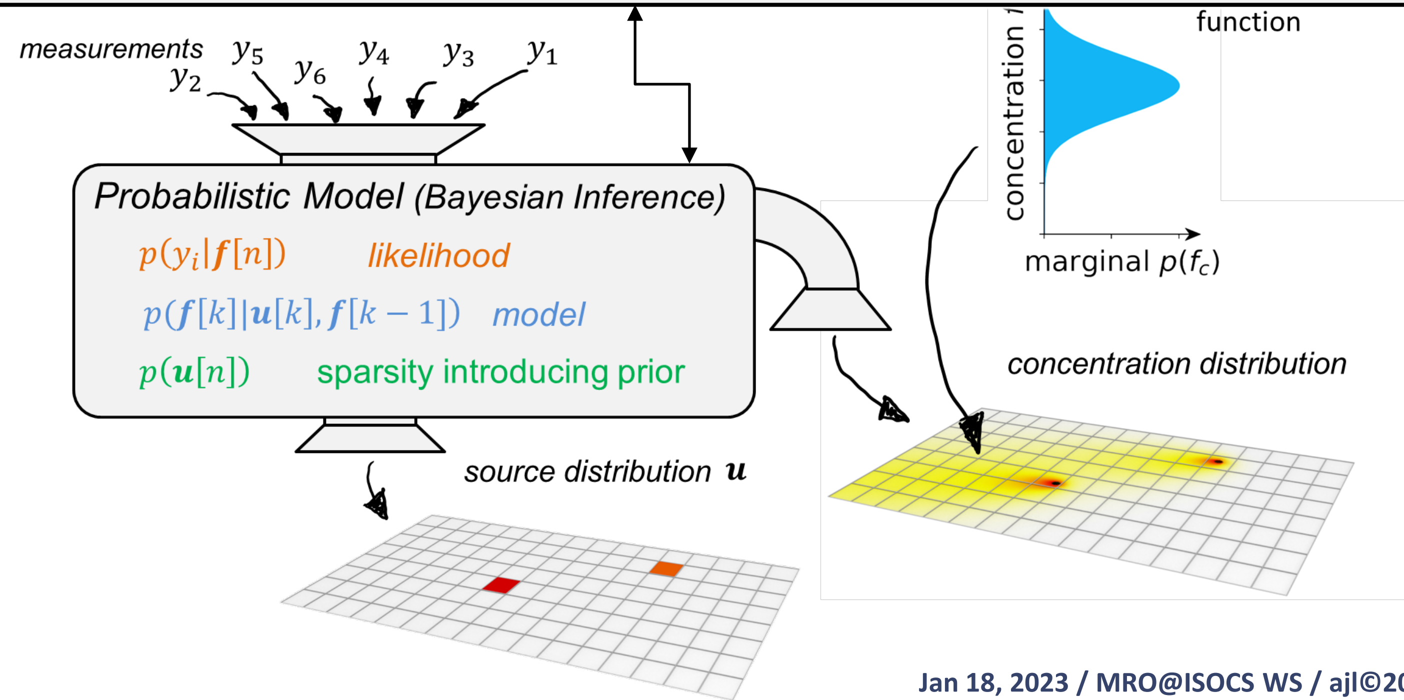
$\longrightarrow$ sparsity introducing prior PDF $p(\boldsymbol{u}[n]) \propto$ Student's t PDF

Bayesian approach: probability density function (PDF)

$$p(\boldsymbol{f}[n], \boldsymbol{u}[n] | \boldsymbol{y}[n], \boldsymbol{f}[n-1]) \propto \underbrace{p(\boldsymbol{y}|\boldsymbol{f}[n], \boldsymbol{v}_1[n], \boldsymbol{v}_2[n])}_{\text{State likelihood}} \underbrace{p(\boldsymbol{f}[n]|\boldsymbol{v}_1[n], \boldsymbol{v}_2[n], \boldsymbol{u}[n], \boldsymbol{f}[n-1])}_{\text{Relaxed model}} \underbrace{p(\boldsymbol{v}_1[n], \boldsymbol{v}_2[n])\, p(\boldsymbol{u}[n])}_{\text{Prior Information}}$$

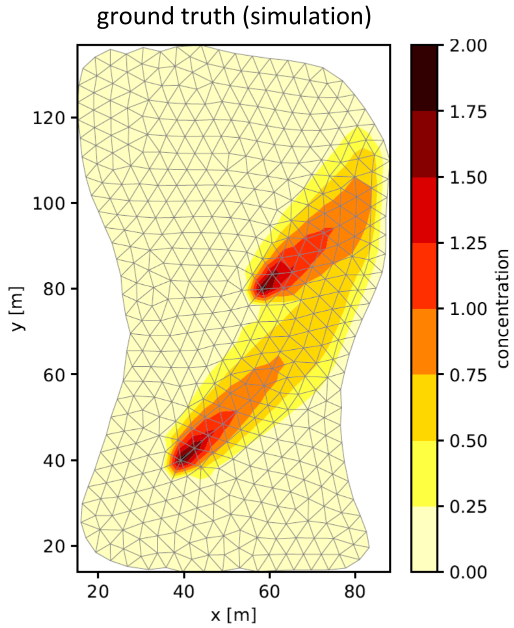






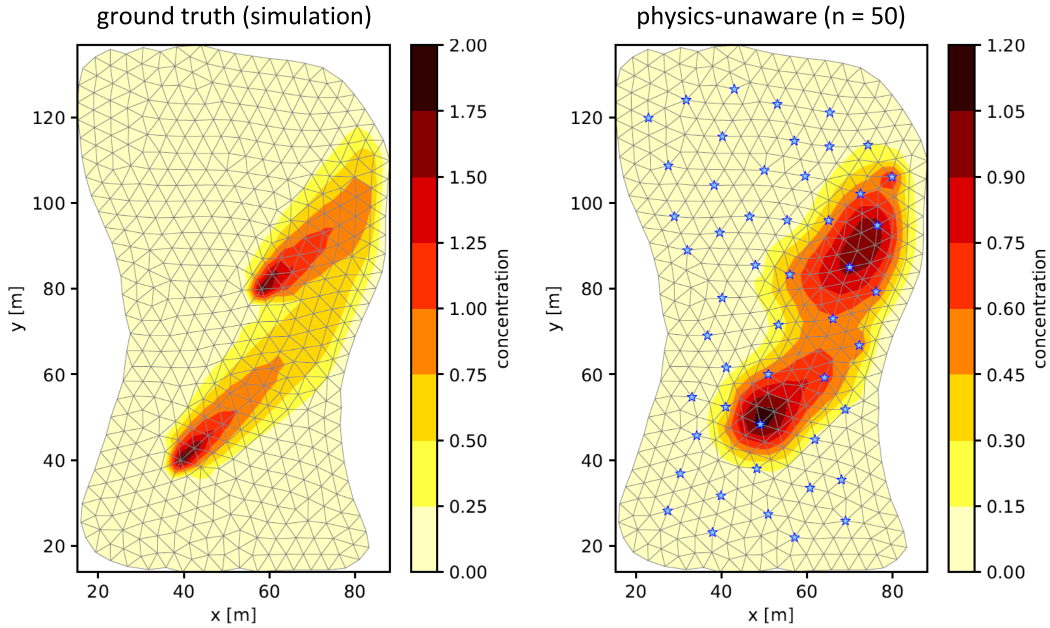
INTEGRATING PDE KNOWLEDGE FROM PHYSICS INTO GSL

- Simulation Results: GSL & GDM & Exploration



Integrating PDE Knowledge From Physics Into GSL

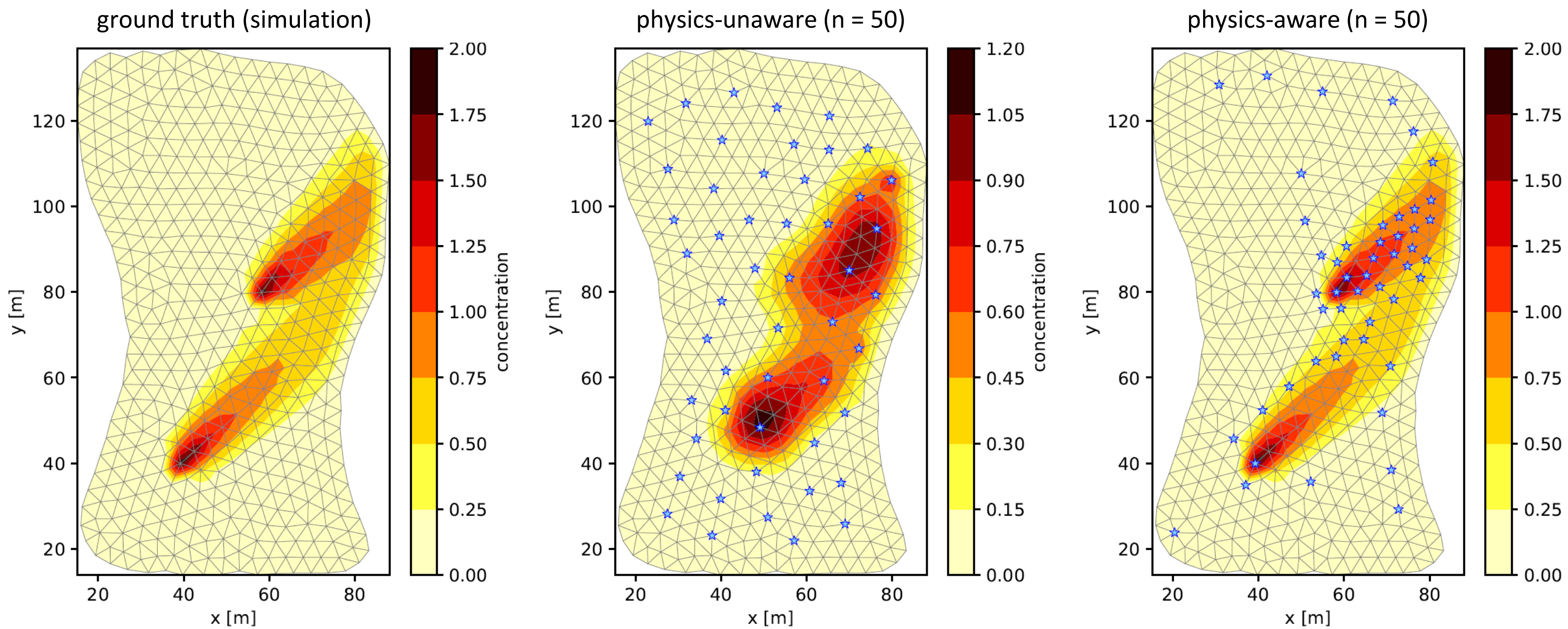
- Simulation Results: GSL & GDM & Exploration



Integrating PDE Knowledge From Physics Into GSL

- Simulation Results: GSL & GDM <= Exploration

$$-\kappa\nabla^2 f(\boldsymbol{x}) + (\boldsymbol{w}(\boldsymbol{x})\cdot\nabla)f(\boldsymbol{x}) = u(\boldsymbol{x}), \quad \boldsymbol{x}\in\Omega$$



Integrating PDE Knowledge From Physics Into GSL

- Airflow Mapping <= Exploration

Incompressible Navier-Stokes equations

$$(\boldsymbol{w}(\boldsymbol{x}) \cdot \nabla)\boldsymbol{w}(\boldsymbol{x}) - \nu \nabla^2 \boldsymbol{w}(\boldsymbol{x}) = -\frac{1}{\rho} \nabla p(\boldsymbol{x})$$

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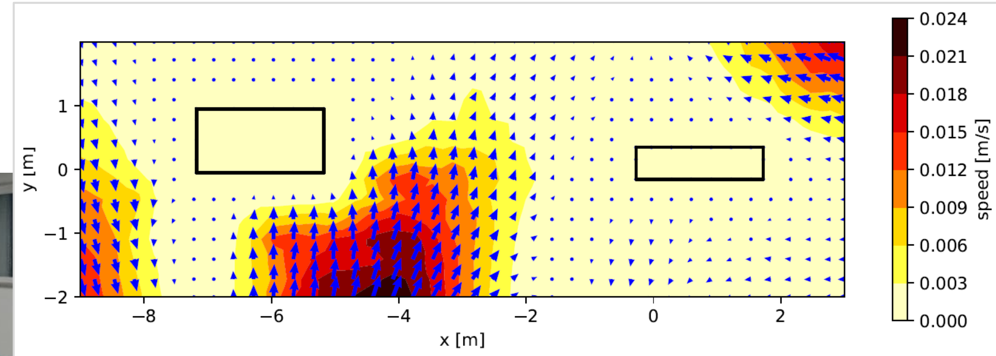

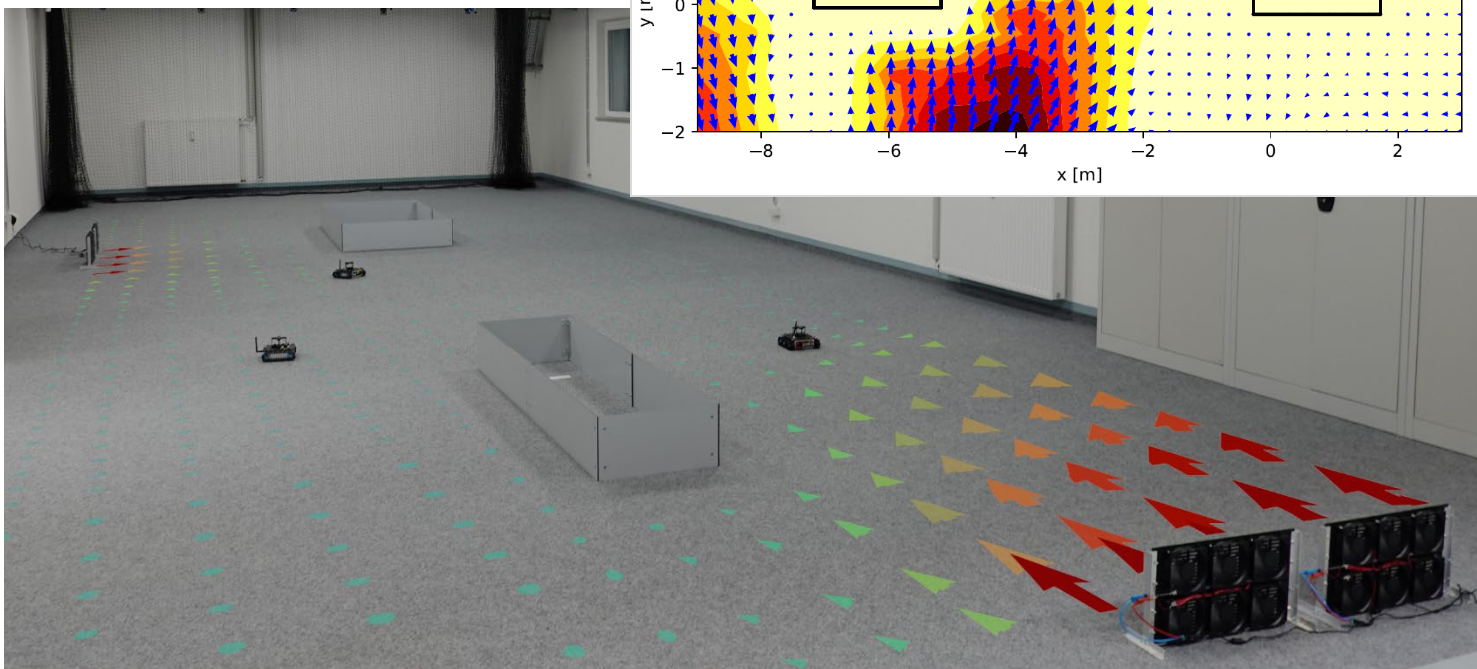

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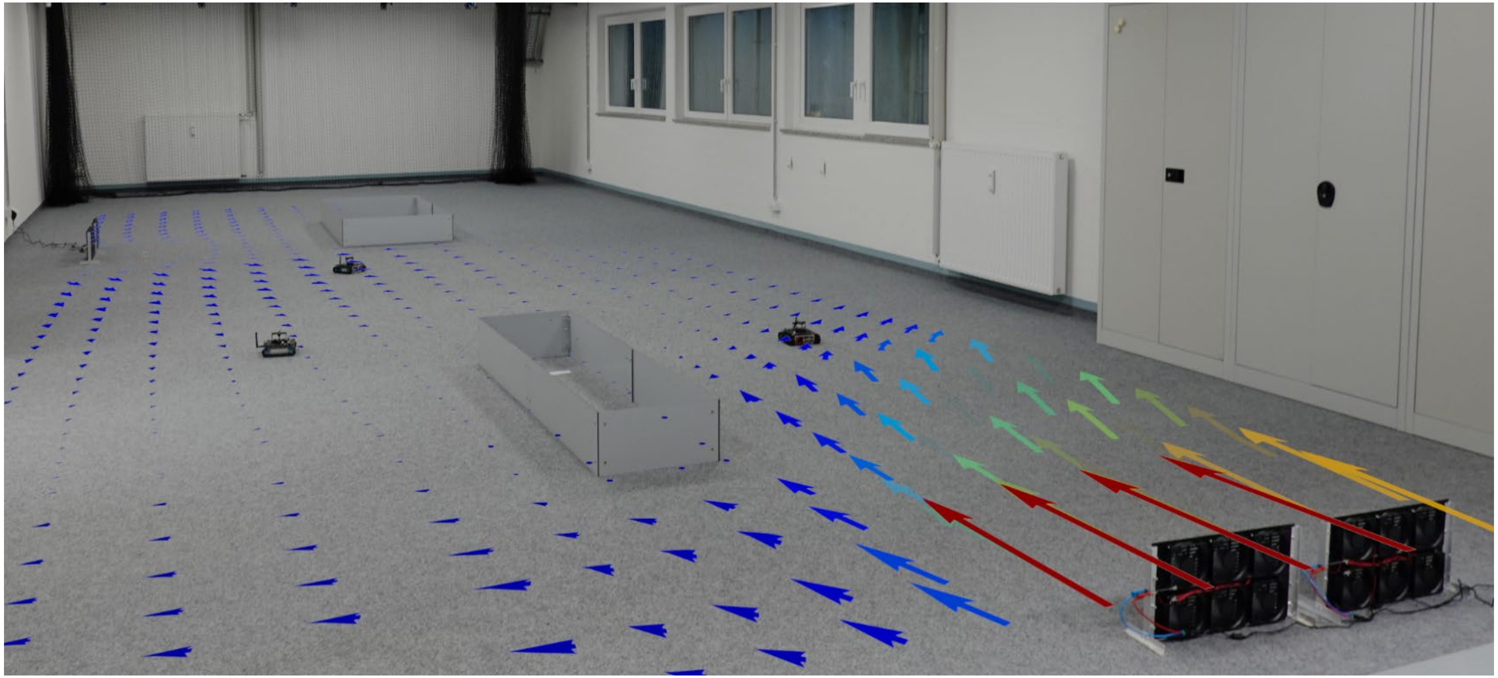

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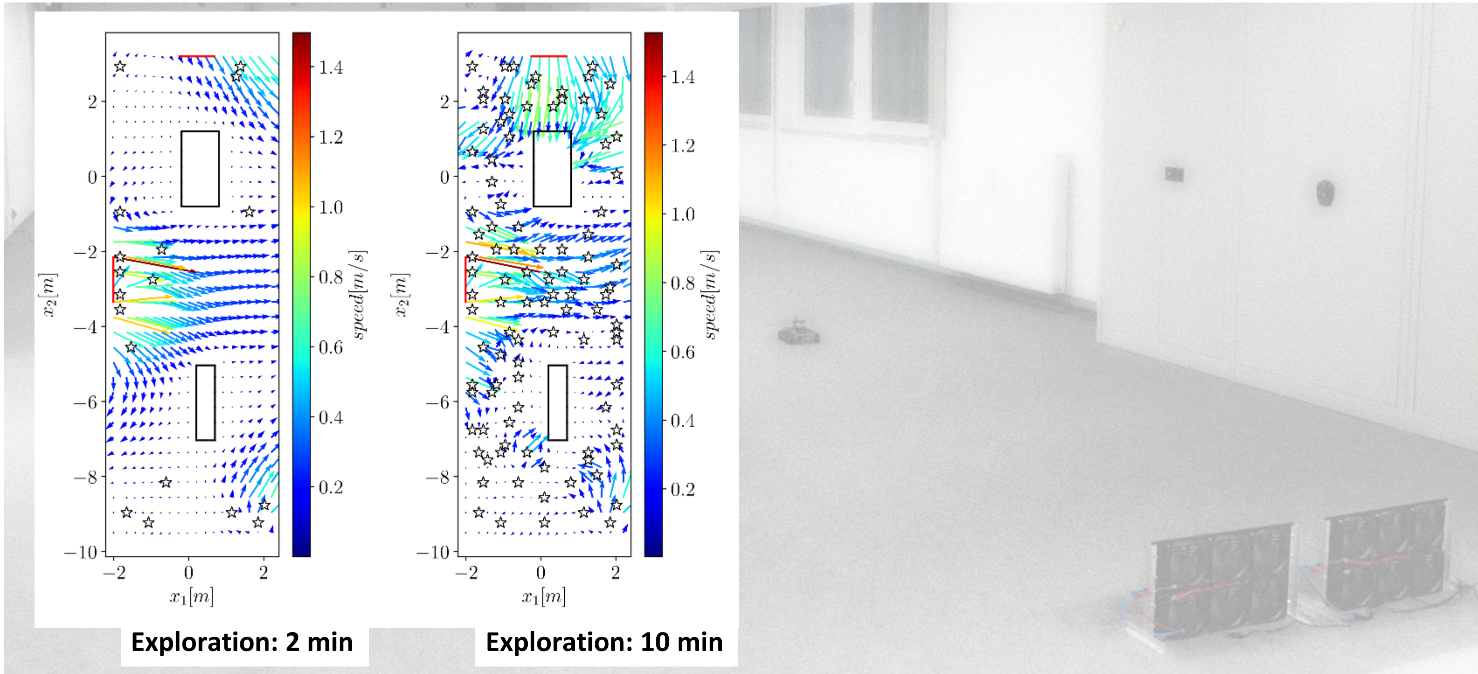

CHALLENGES

- Turbulent Gas Dispersal & Sparse Sampling
- Broad-spectrum gas sensors (e-nose) have disadvantages
  - Often long response/recovery time => Steady state never reached!
  - Individual sensor characteristics
  - Cross-sensitivity, e.g., to temperature and humidity
  - Drift

CHALLENGES

- parse Sampling
- s (e-nose) have disadvantages
- ry time => Steady state never reached!
- tics
- peratu
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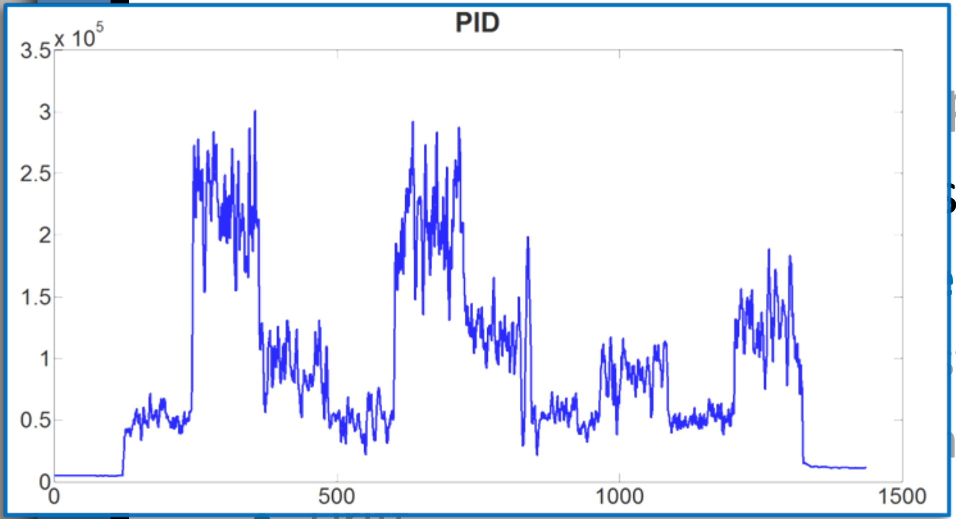
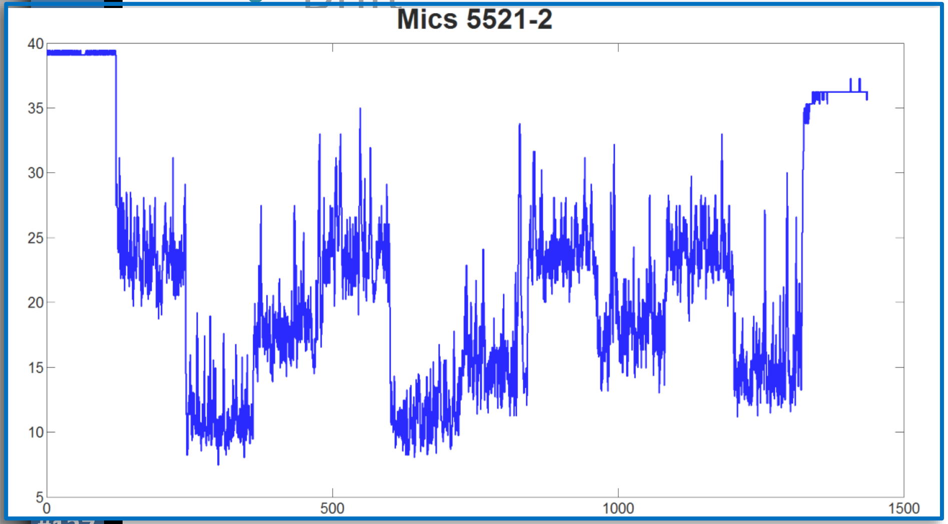
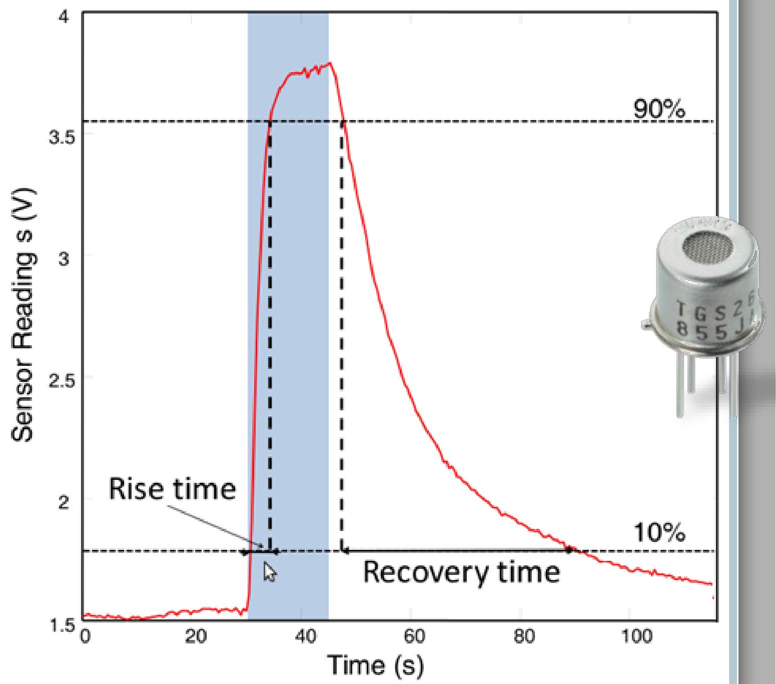
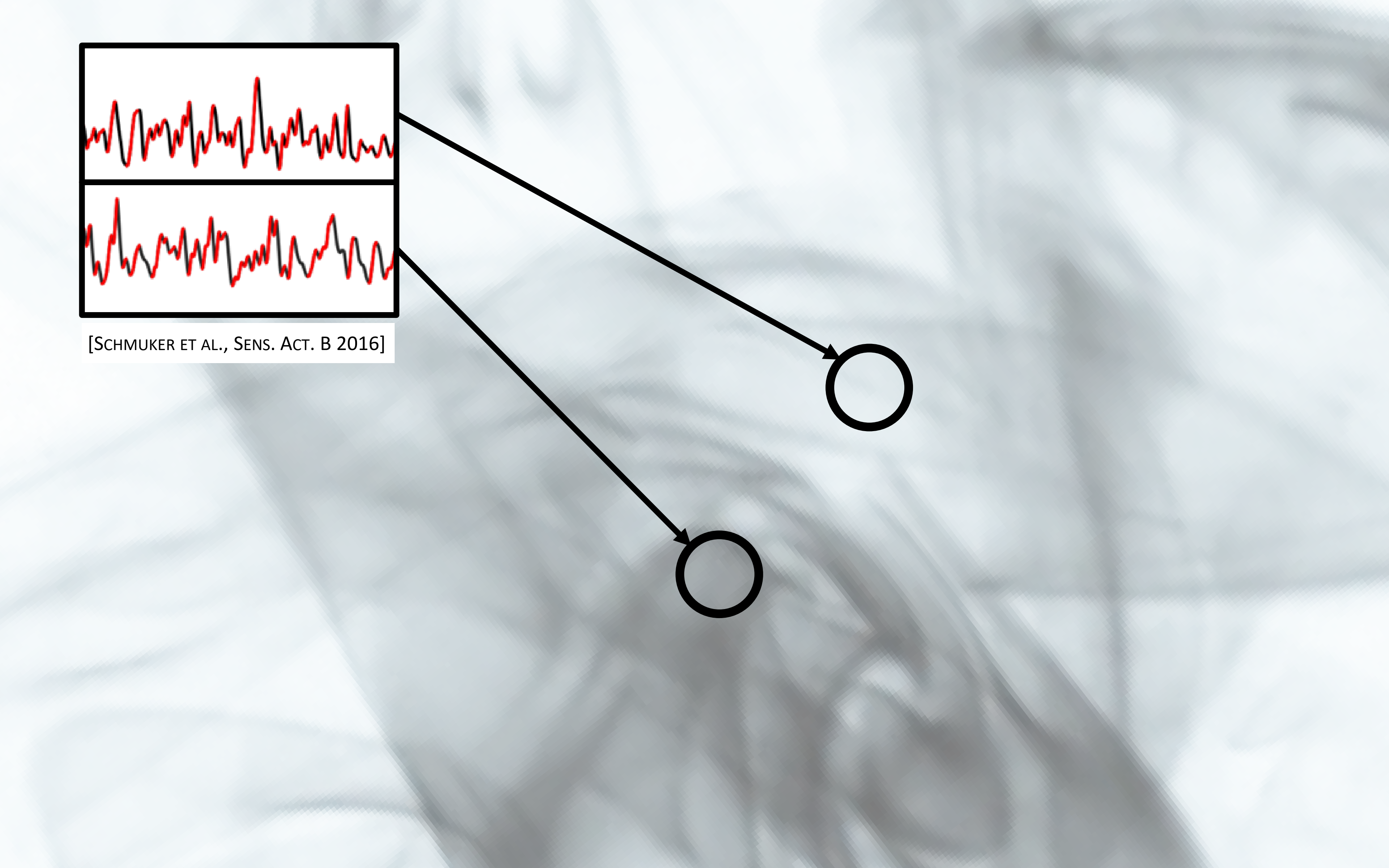






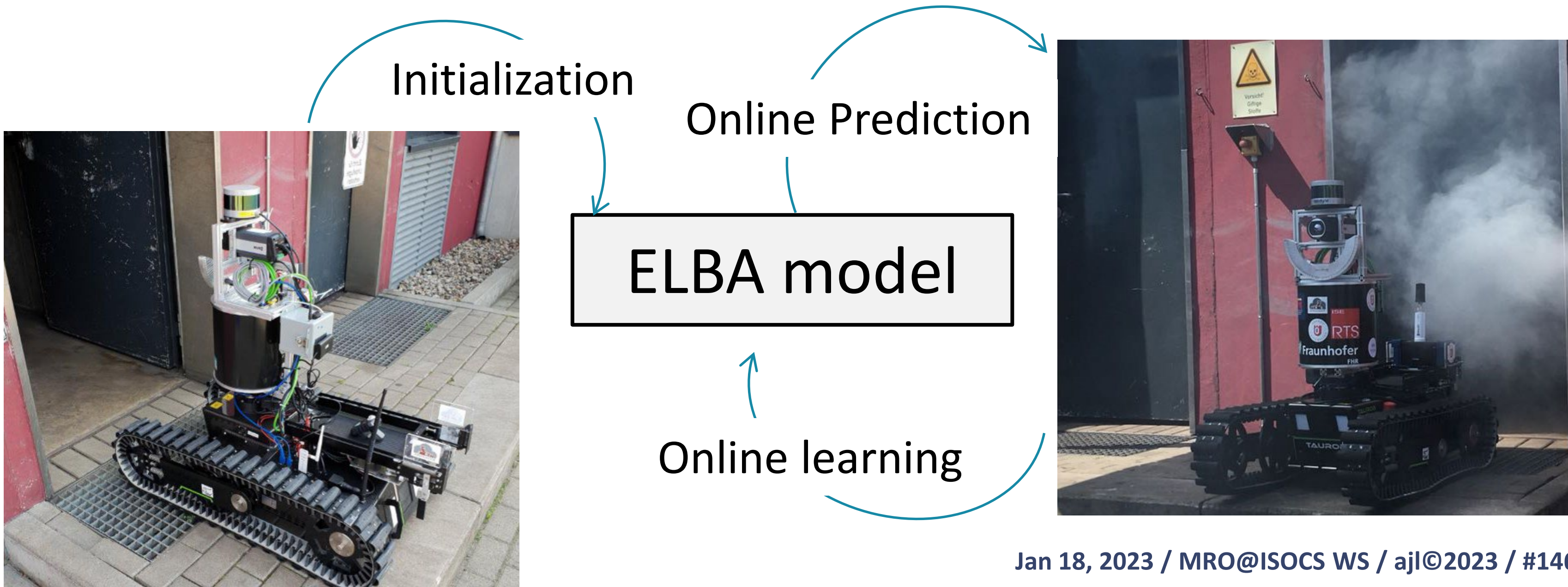


[Schmuker et al., Sens. Act. B 2016]

[Fan et al., ISOEN 2019]

Mobile Robot Olfaction, Ongoing Work

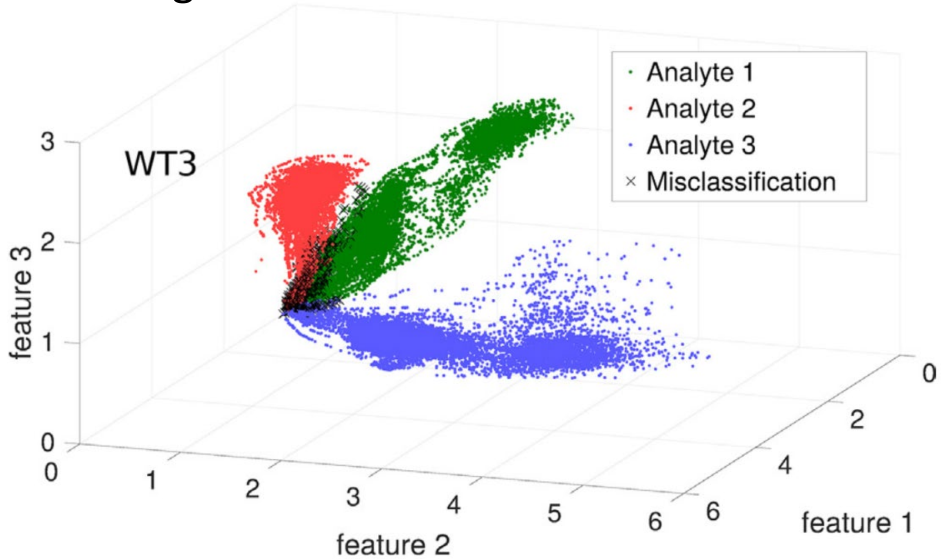
- Presence of *A Priori* Unknown Gases (APUG), Gas Detection
  - Ensemble Learning Based Approach for gas detection (ELBA)
    - Initialization with clean air
    - Learns the ensemble online with self-labeled data compensating for possible sensor drift

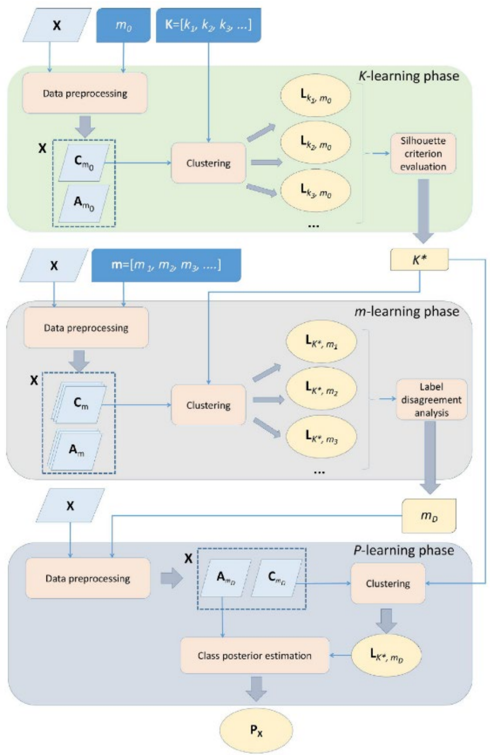


MOBILE ROBOT OLFACTION, ONGOING WORK

[FAN ET AL., S&A:B 2018]
[FAN ET AL., IEEE SENSORS 2016]

- Presence of *A Priori* Unknown Gases, Gas Discrimination
  - KmP algorithm for unsupervised gas discrimination
    - Clustering approach that can infer the number of chemical compounds K, and learn a probabilistic representation of the class labels P for the a given environment





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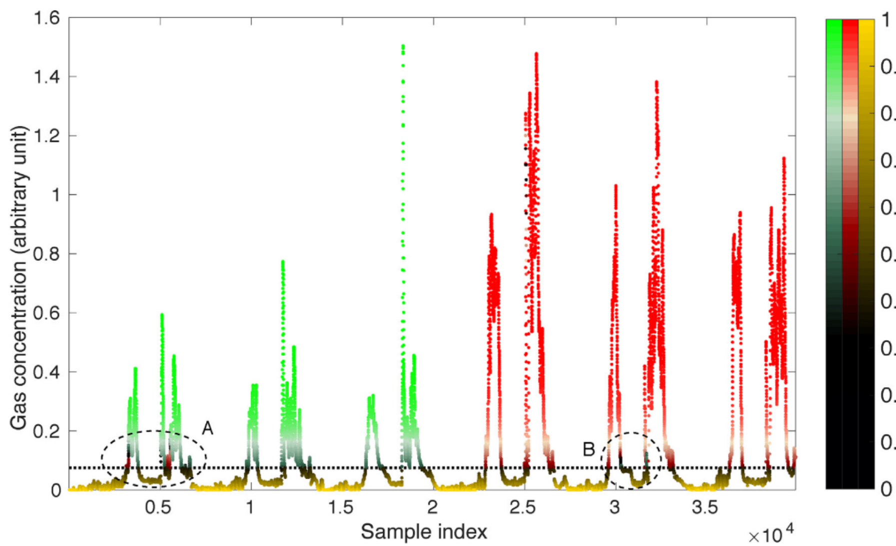
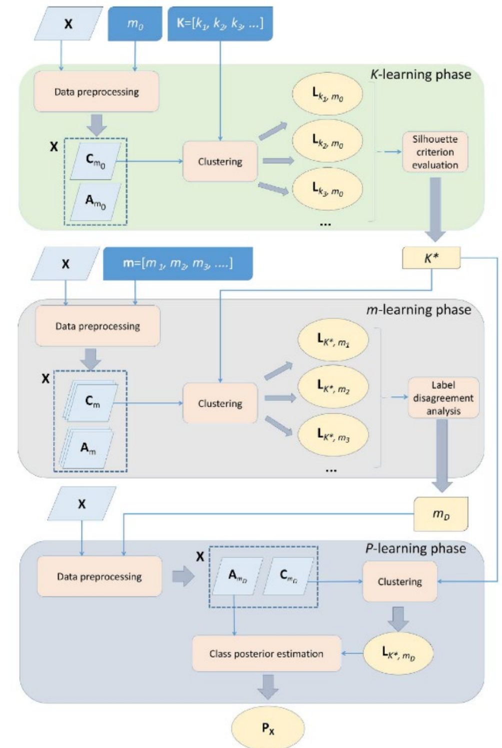
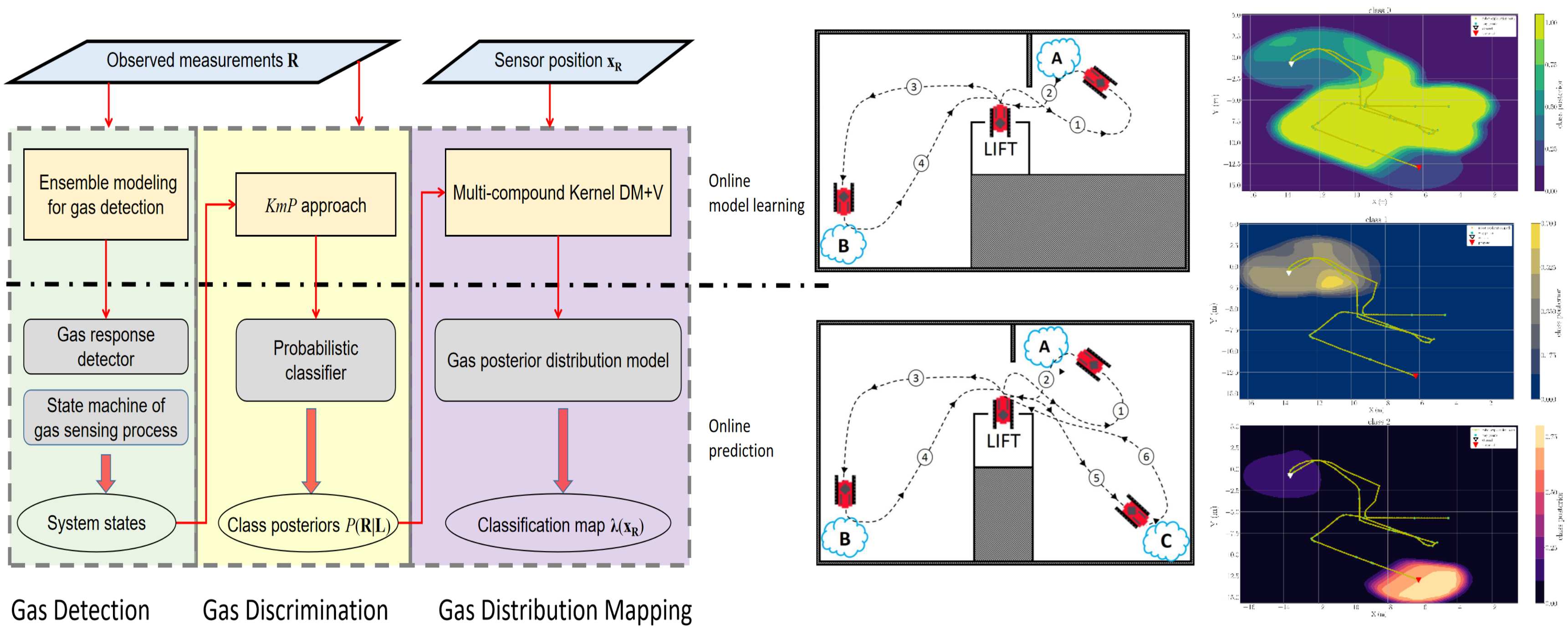




Mobile Robot Olfaction, Ongoing Work

[Fan et al., Sensors 2019]
[Xing et al., IEEE Sensors, 2019]

- Presence of APUG, Gas Distribution Mapping
  - Gas Distribution Mapping in the presence of unknown components



CHALLENGES

- Turbulent Gas Dispersal & Sparse Sampling
- Broad-spectrum gas sensors (e-nose) have disadvantages
- Presence of A Priori Unknown Gases
- Gas sensing with UAVs
  - Superior mobility and deployability comes at a price ...

Challenges – Gas Sensing wit UAVs

CHALLENGES

- Turbulent Gas Dispersal & Sparse Sampling
- Broad-spectrum gas sensors (e-nose) have disadvantages
- Presence of A Priori Unknown Gases
- Gas sensing with UAVs
  - Superior mobility and deployability comes at a price …
    - => Use smaller drones
    - => Use remote sensing on drones

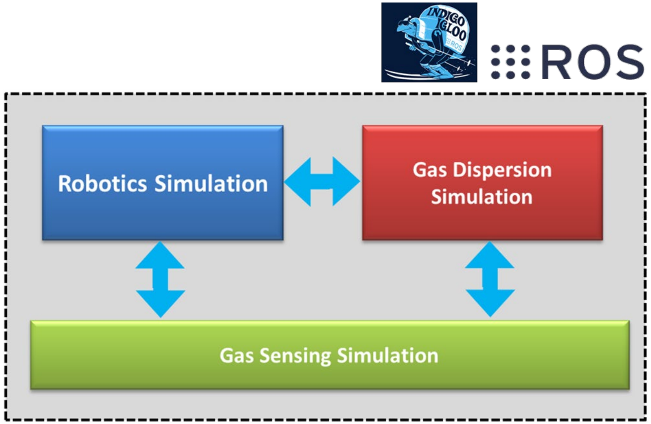
09:30-10:30 Agustín Gutiérrez-Gálvez (University of Barcelona)
Aerial monitoring of pollution and odour
11:30-10:30 Patrick P. Neumann (BAM)
Aerial-based Gas Tomography

CHALLENGES

- Turbulent Gas Dispersal & Sparse Sampling
- Broad-spectrum gas sensors (e-nose) have disadvantages
- Presence of A Priori Unknown Gases
- Gas sensing with UAVs
- Hard to measure ground truth independently

Mobile Robot Olfaction, Ongoing Work

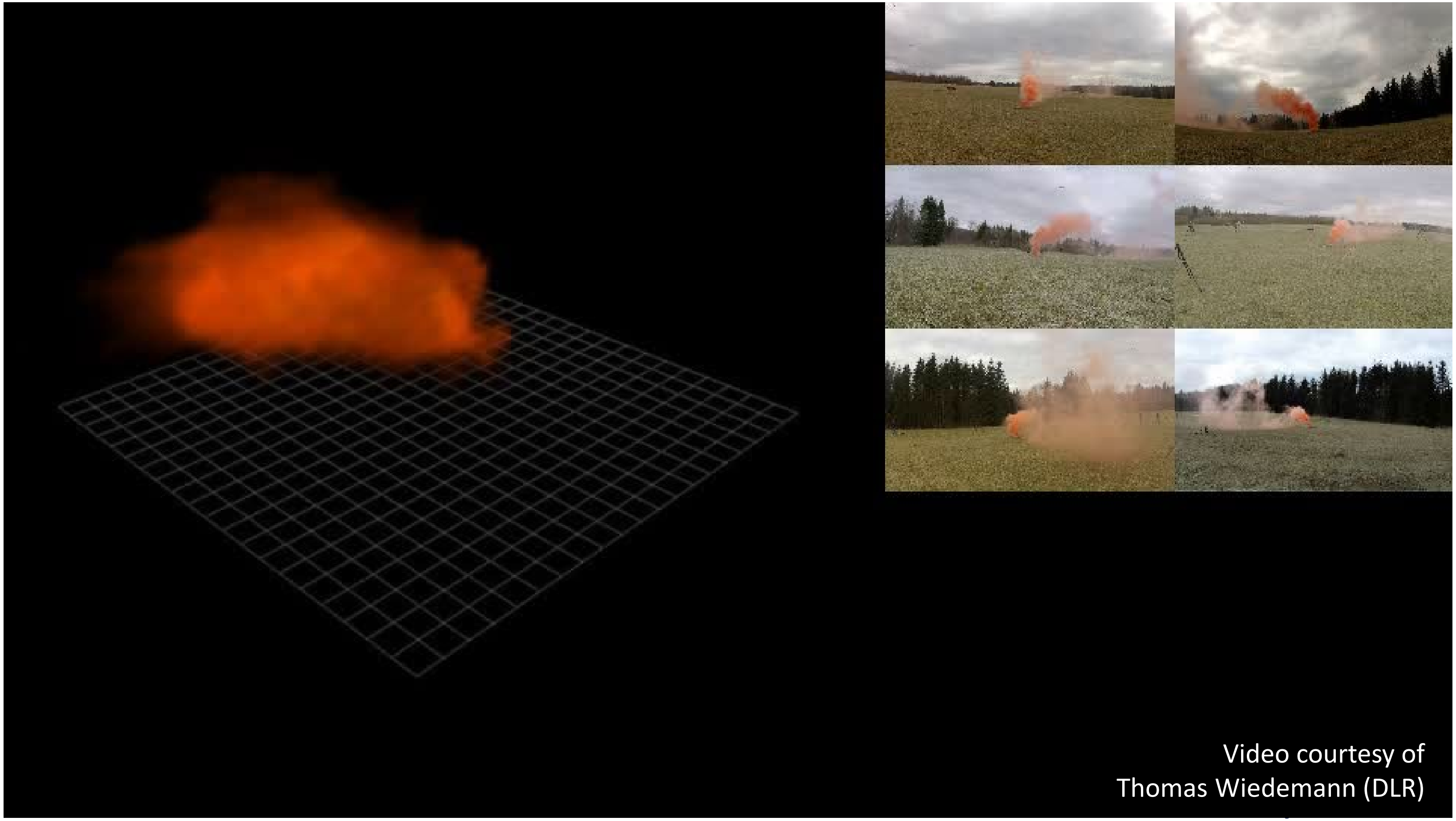
- Gas Dispersal Simulator GADEN



[Monroy et al., Sensors 2017]

Mobile Robot Olfaction, Ongoing Work

- Optical Plume Reconstruction



Video courtesy of
Thomas Wiedemann (DLR)

MR&O
MOBILE ROBOTICS & OLFACTION

ÖREBRO UNIVERSITY

Thank you for your attention!

MODELLING AND SENSOR PLANNING FOR ENVIRONMENTAL MONITORING WITH GAS-SENSITIVE MOBILE ROBOTS

Achim J. Lilienthal et al.

MR&O
MOBILE ROBOTICS & OLFACTION

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