MR&O
MOBILE ROBOTICS & OLFACTION

aass

Örebro Universitet

Dense Environmental Monitoring with Stationary and Mobile Sensing Nodes

Tutorial Course: Distributed Chemical Sensing For Remote Environmental Monitoring

Achim J. Lilienthal

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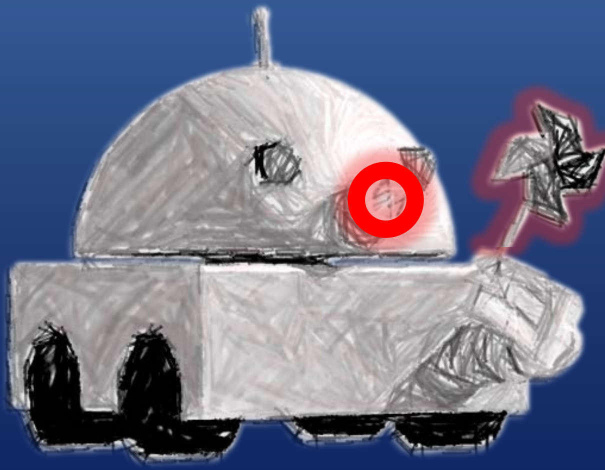
achim.lilienthal@oru.se

MR&O MOBILE ROBOTICS & OLFACTION

Dense Environmental Monitoring w
Stationary and Mobile Sensing Nodes

Tutorial Course: Distributed Chemical Sensing
For Remote Environmental Monitoring

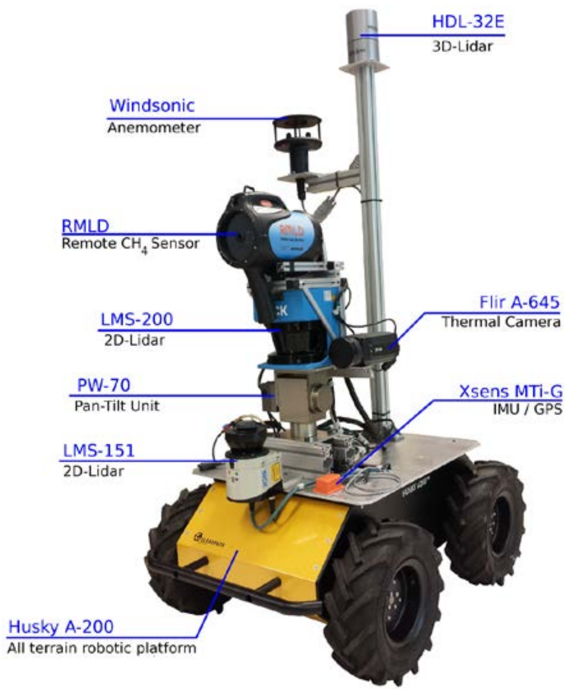
A Brief Introduction to Mobile Robot Olfaction

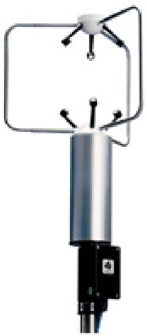


Basic Idea

- Combine autonomous robots with ...
- ... gas sensors and ...
- ... possibly other relevant sensors

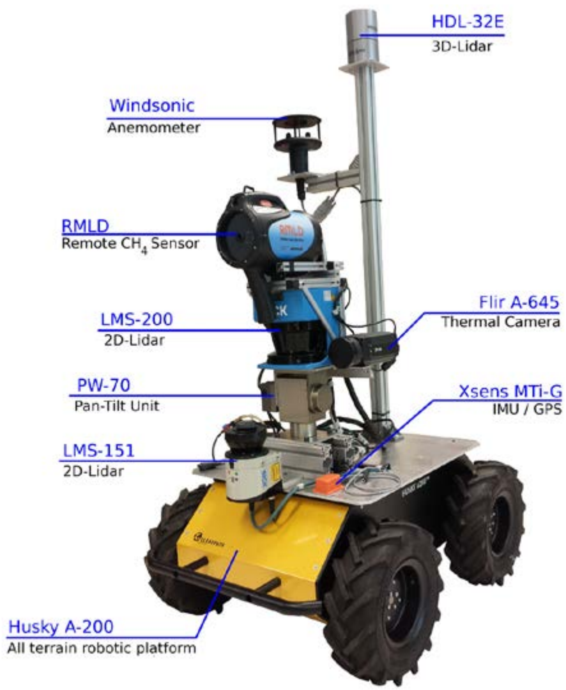
[Hernandez Bennets et al., FrontNeuroEng 2012]
[Lilienthal et al., Sensors 2006]





▪ Basic Idea

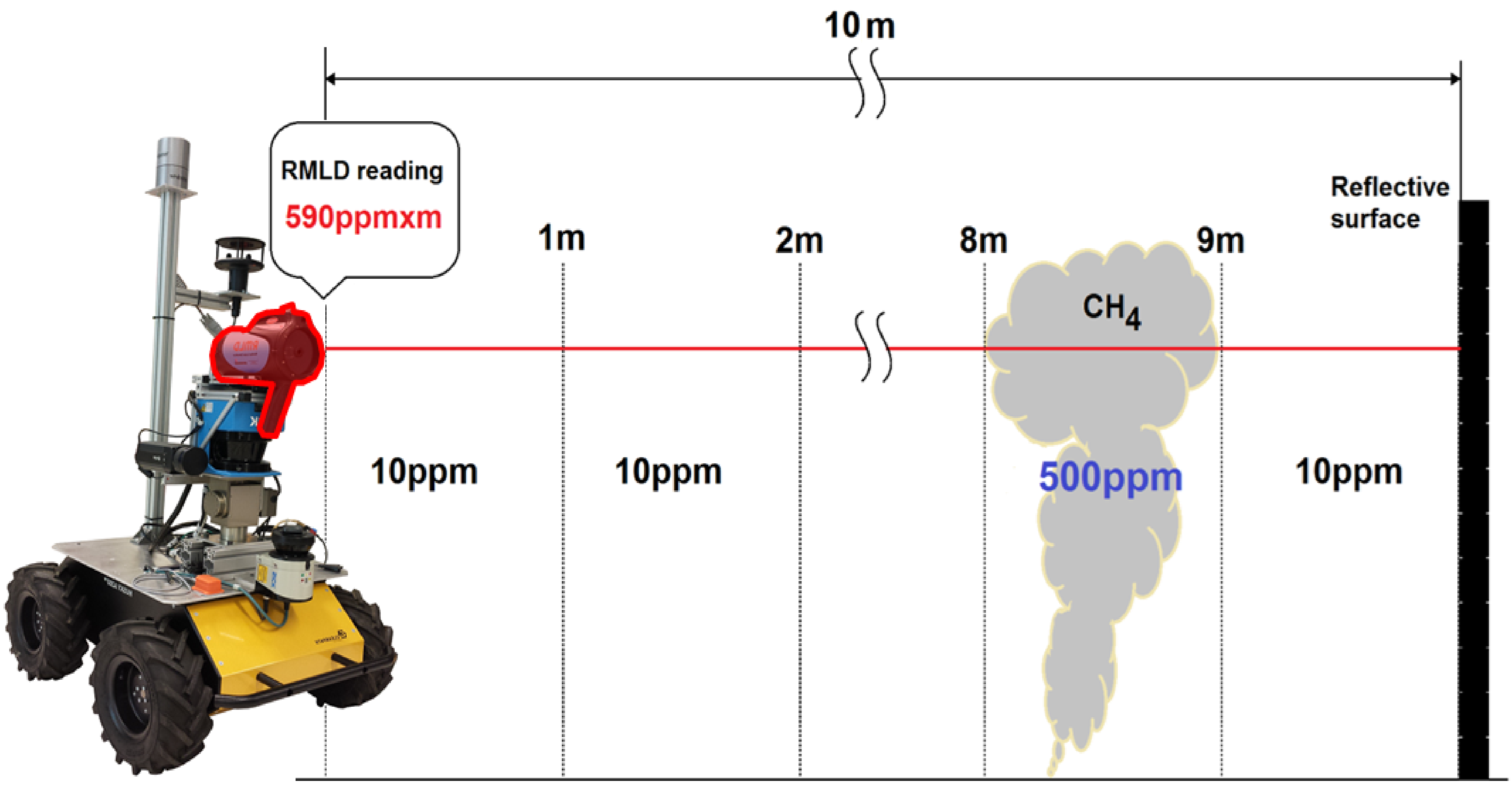
- Combine autonomous robots with ...
- ... gas sensors and ...
- ... possibly other relevant sensors
- **Gas-Sensitive Robot "="**
  Controllable Mobile Sensor Node



=

[Lilienthal et al., Sensors 2006]

- **Subtasks in Mobile Robot Olfaction**
  - Gas detection (gas finding)
    - Detecting an increased concentration of a target gas



[Arain et al., ICRA 2015]
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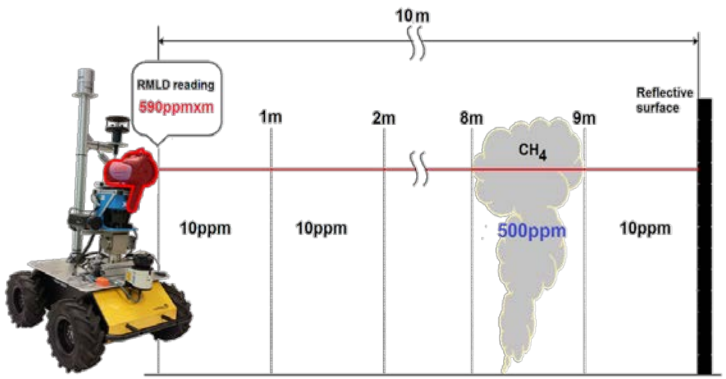

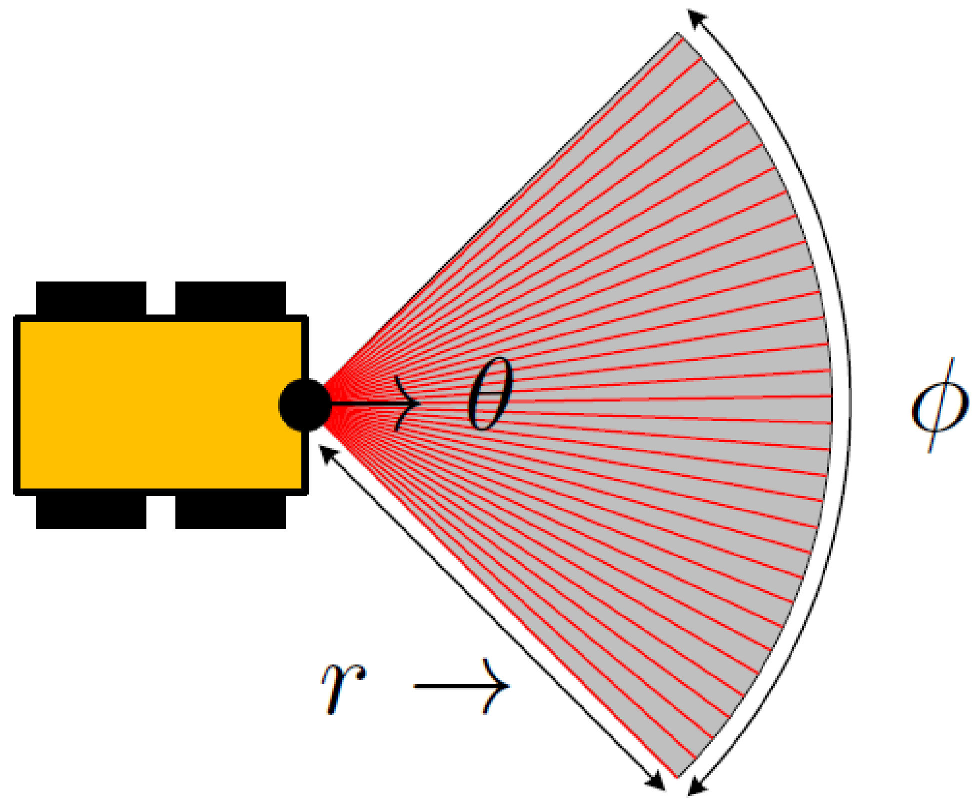

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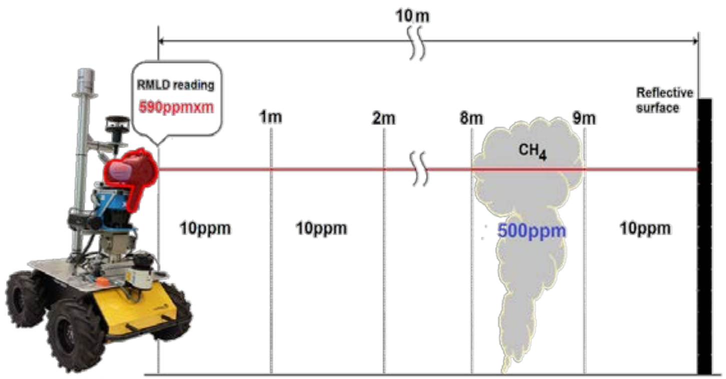

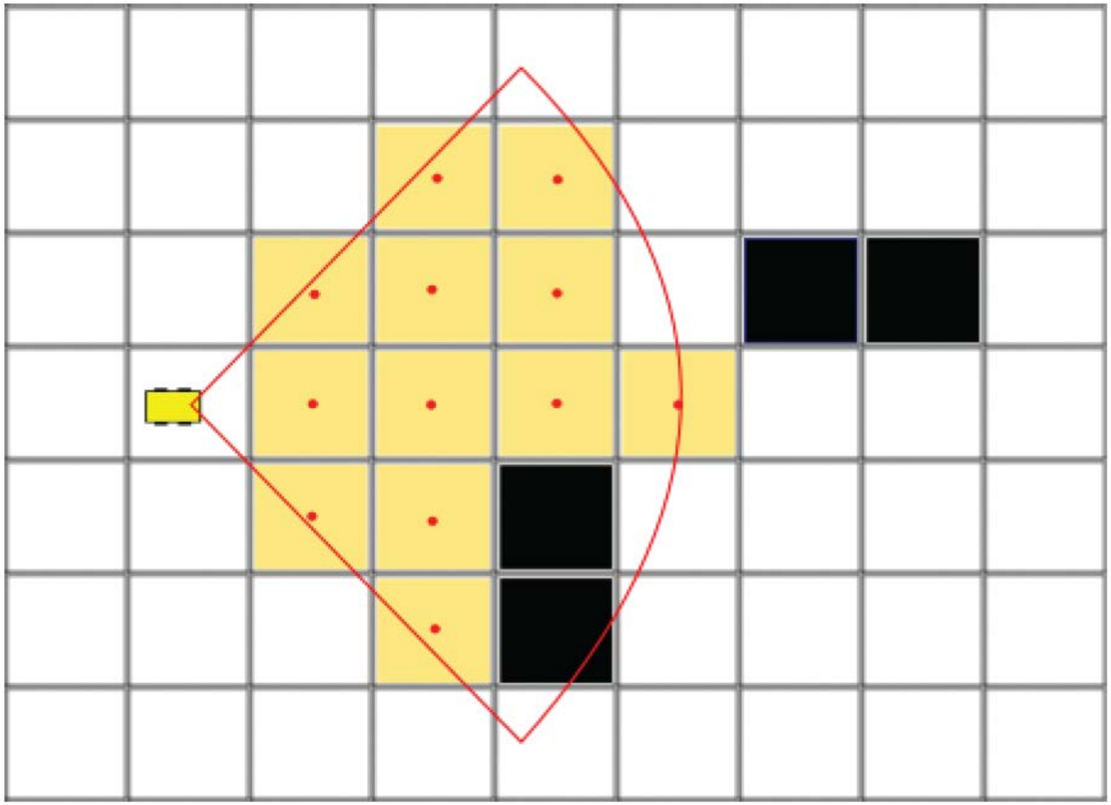

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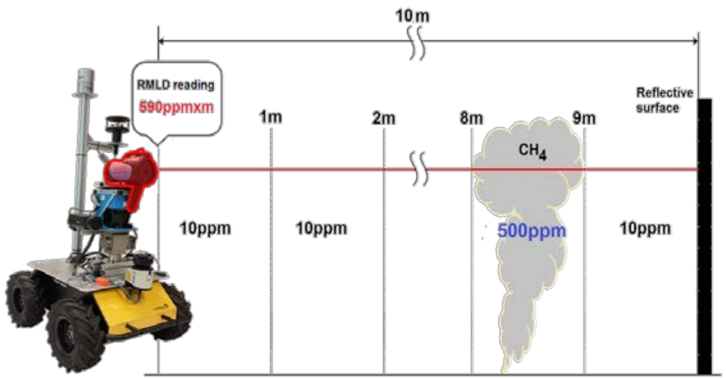

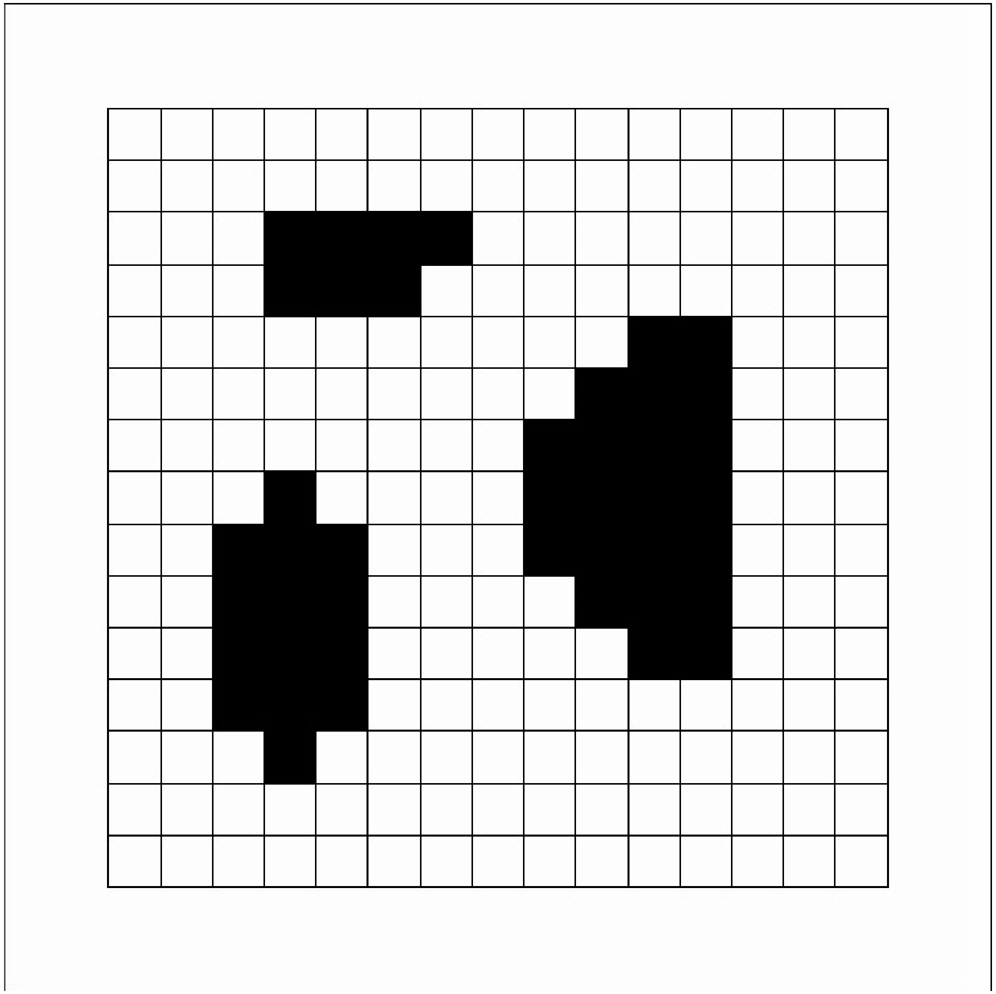

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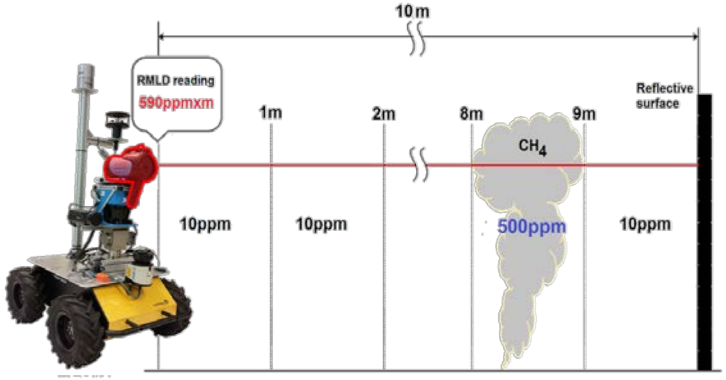
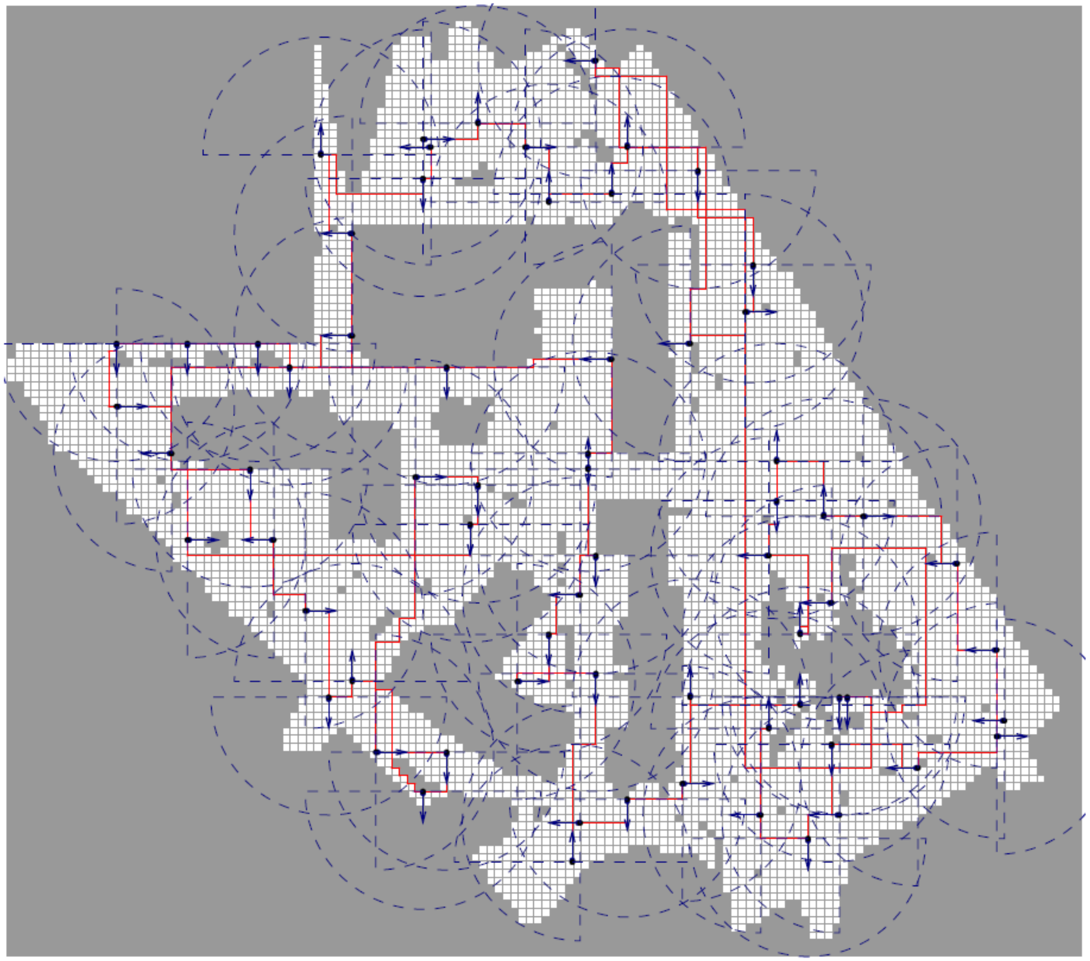
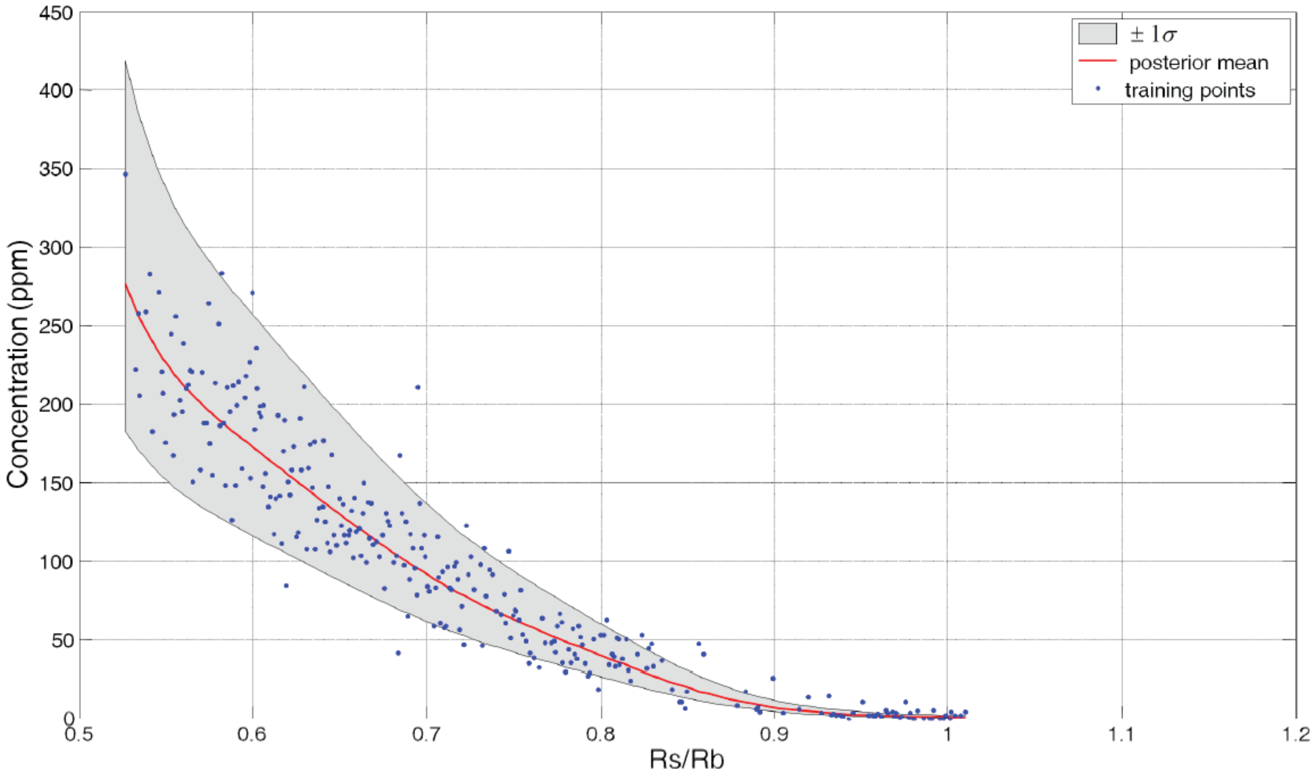




Subtasks in Mobile Robot Olfaction

[González Monroy et al., S&A:B 2013]

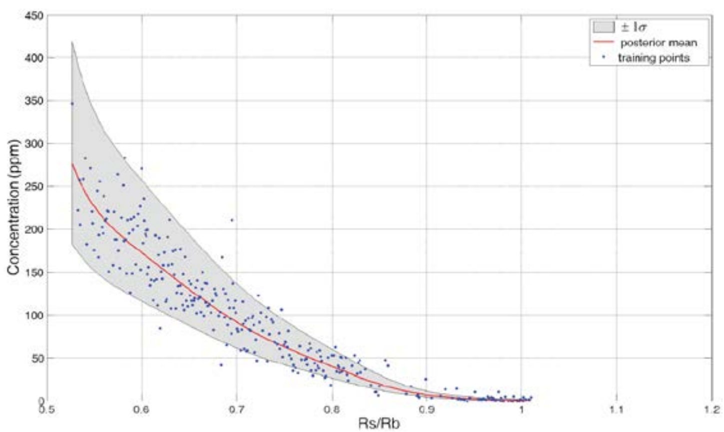
- Gas detection (gas finding)
- "Odour" discrimination and concentration estimation
  - Sensor calibration

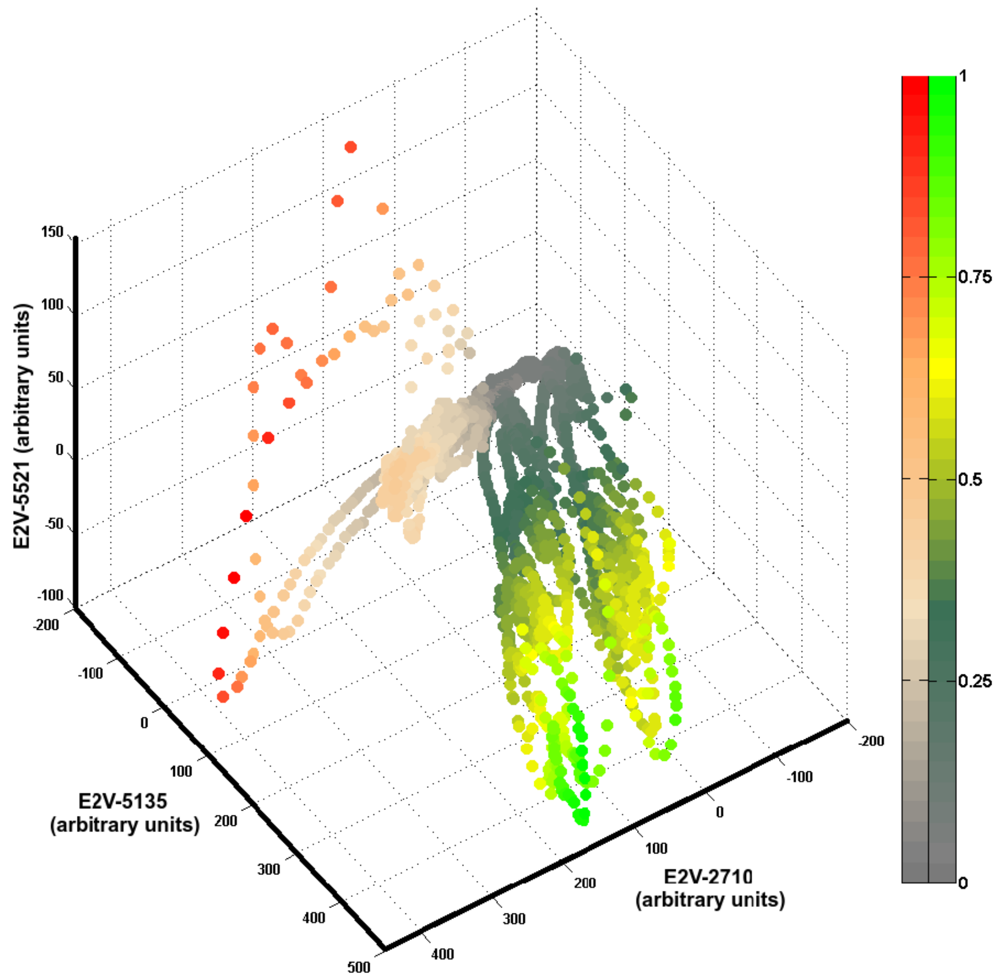


Subtasks in Mobile Robot Olfaction

- Gas detection (gas finding)
- "Odour" discrimination and concentration estimation
  - Sensor calibration
  - Pattern recognition

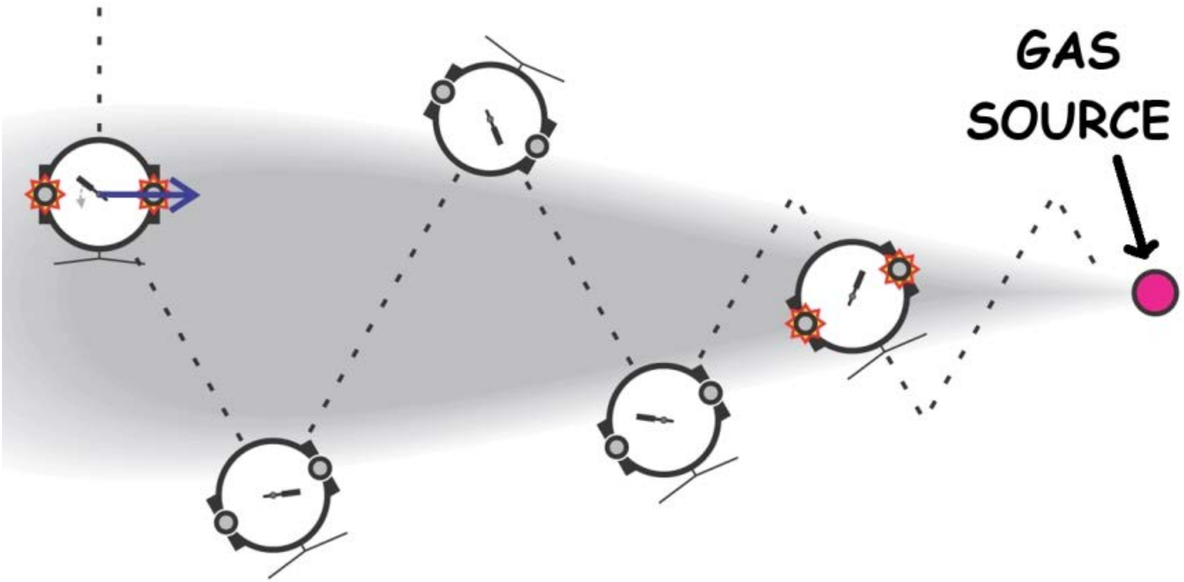
[Hernandez Bennets et al., IEEE Sensors 2014]





▪ Subtasks in Mobile Robot Olfaction

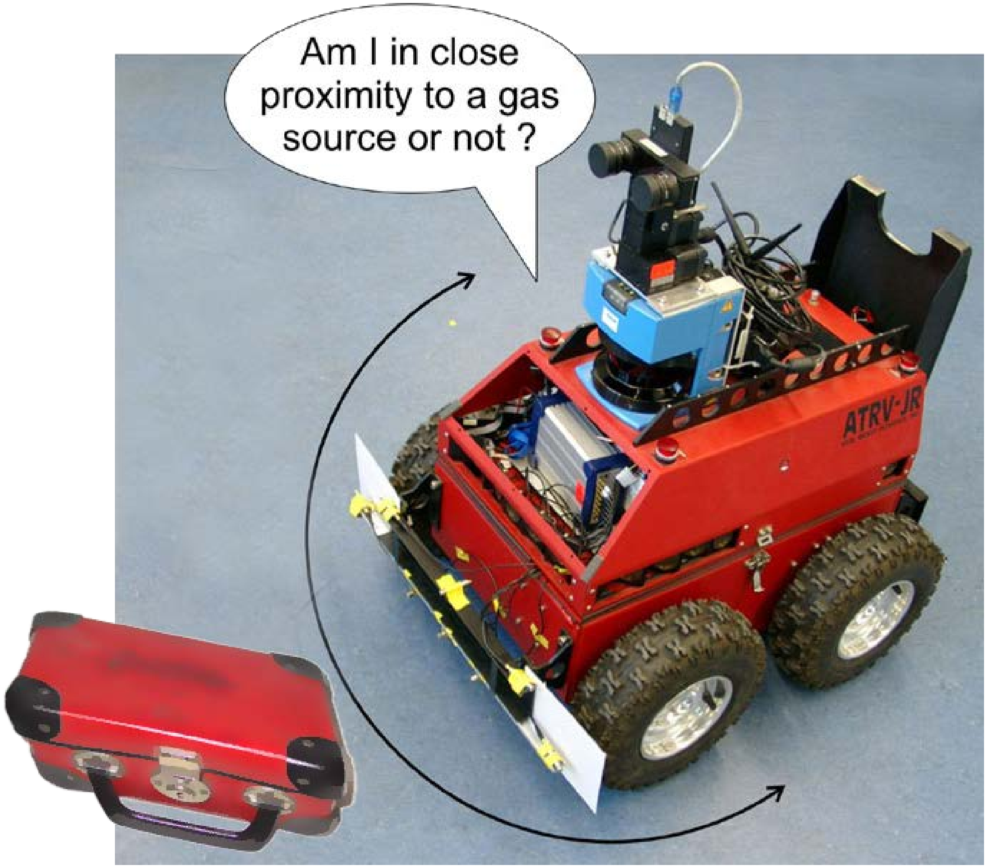
- Gas detection (gas finding)
- "Odour" discrimination and concentration estimation
- Gas source tracking
  - » Following the cues from the sensed gas distribution (eventually using also other sensor modalities) towards the source



from [Lilienthal et al., Sensors 2006]

[Lilienthal et al., ICRA 2004]
[Lilienthal et al., IROS 2004]

- **Subtasks in Mobile Robot Olfaction**
  - Gas detection (gas finding)
  - "Odour" discrimination and concentration estimation
  - Gas source tracking
  - Gas source declaration
    - Determining the certainty that the source has been found



- **Subtasks in Mobile Robot Olfaction**
  - Gas detection (gas finding)
  - "Odour" discrimination and concentration estimation
  - Gas source tracking
  - Gas source declaration

Gas source localisation

Subtasks in Mobile Robot Olfaction

- Gas detection (gas finding)
- "Odour" discrimination and concentration estimation
- Gas source tracking
- Gas source declaration
- Trail guidance
  - Trail following

from [Lilienthal et al., Sensors 2006]

Subtasks in Mobile Robot Olfaction

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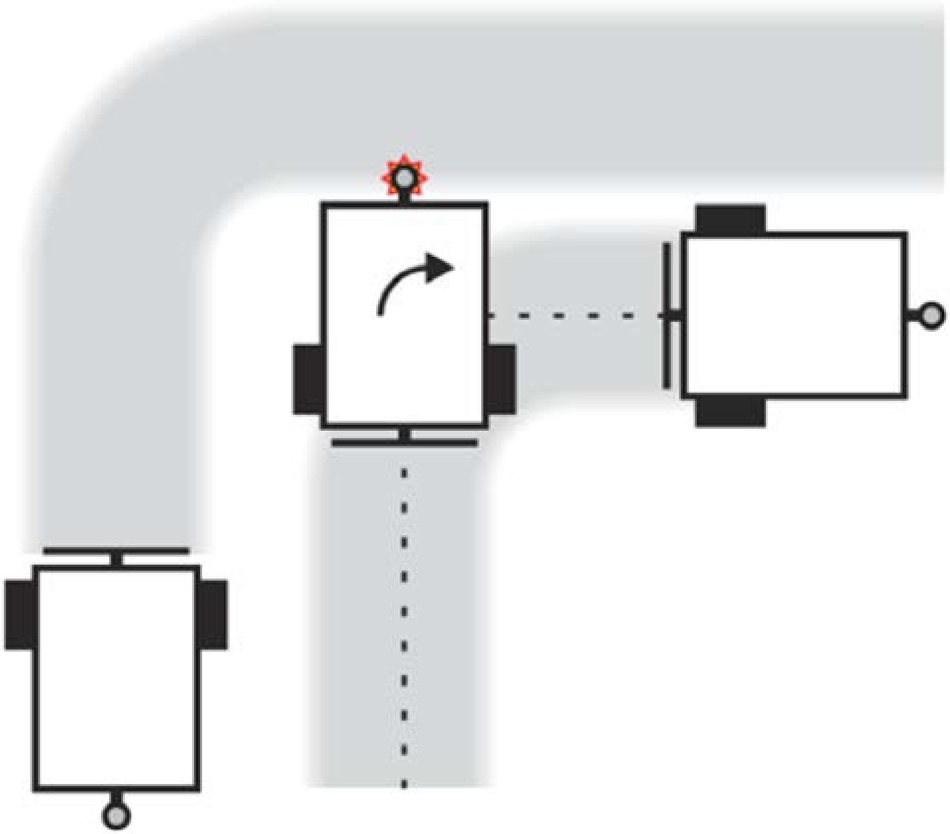
- Gas source tracking
- Gas source declaration
- Trail guidance
  - Trail following
  - Trail avoiding strategies



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Subtasks in Mobile Robot Olfaction

- Gas detection (gas finding)
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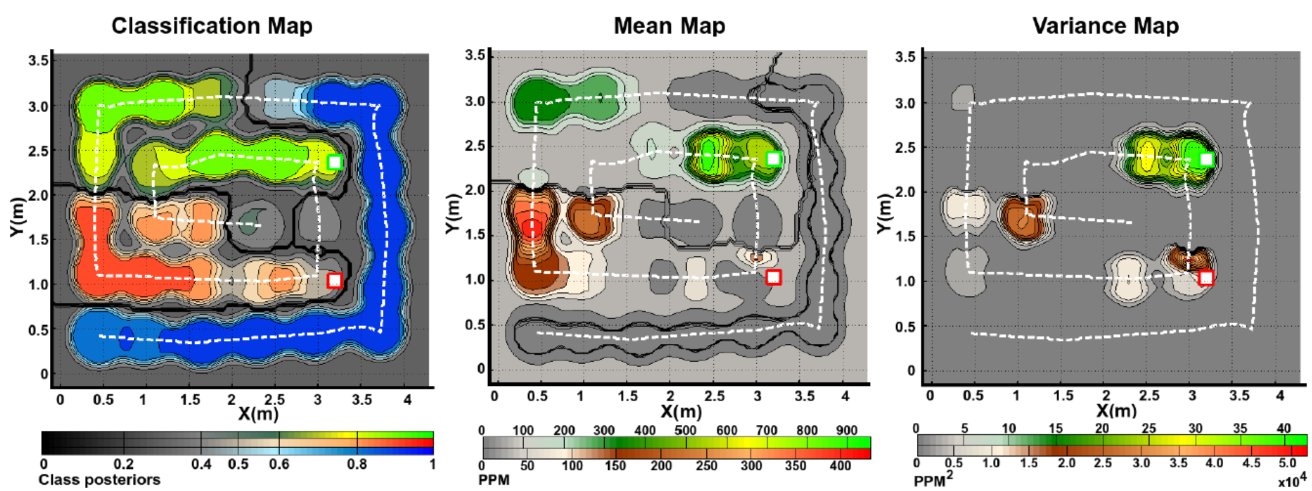
- Trail guidance
  - » Trail following
  - » Trail avoiding strategies
- Gas distribution mapping / Gas distribution modelling

[Hernandez Bennets et al., Sensors 2014]



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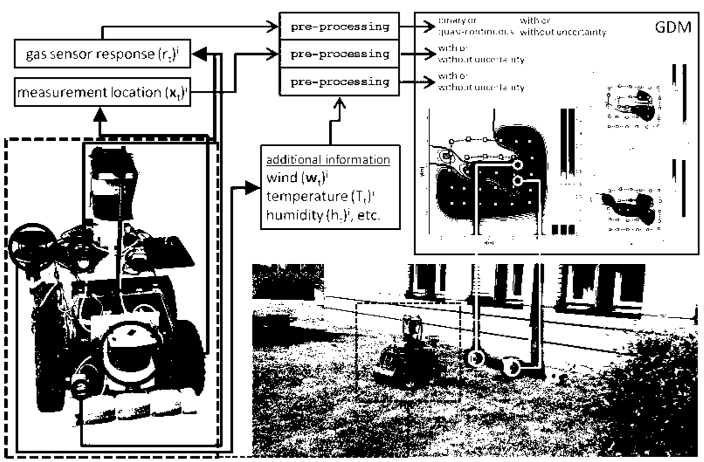
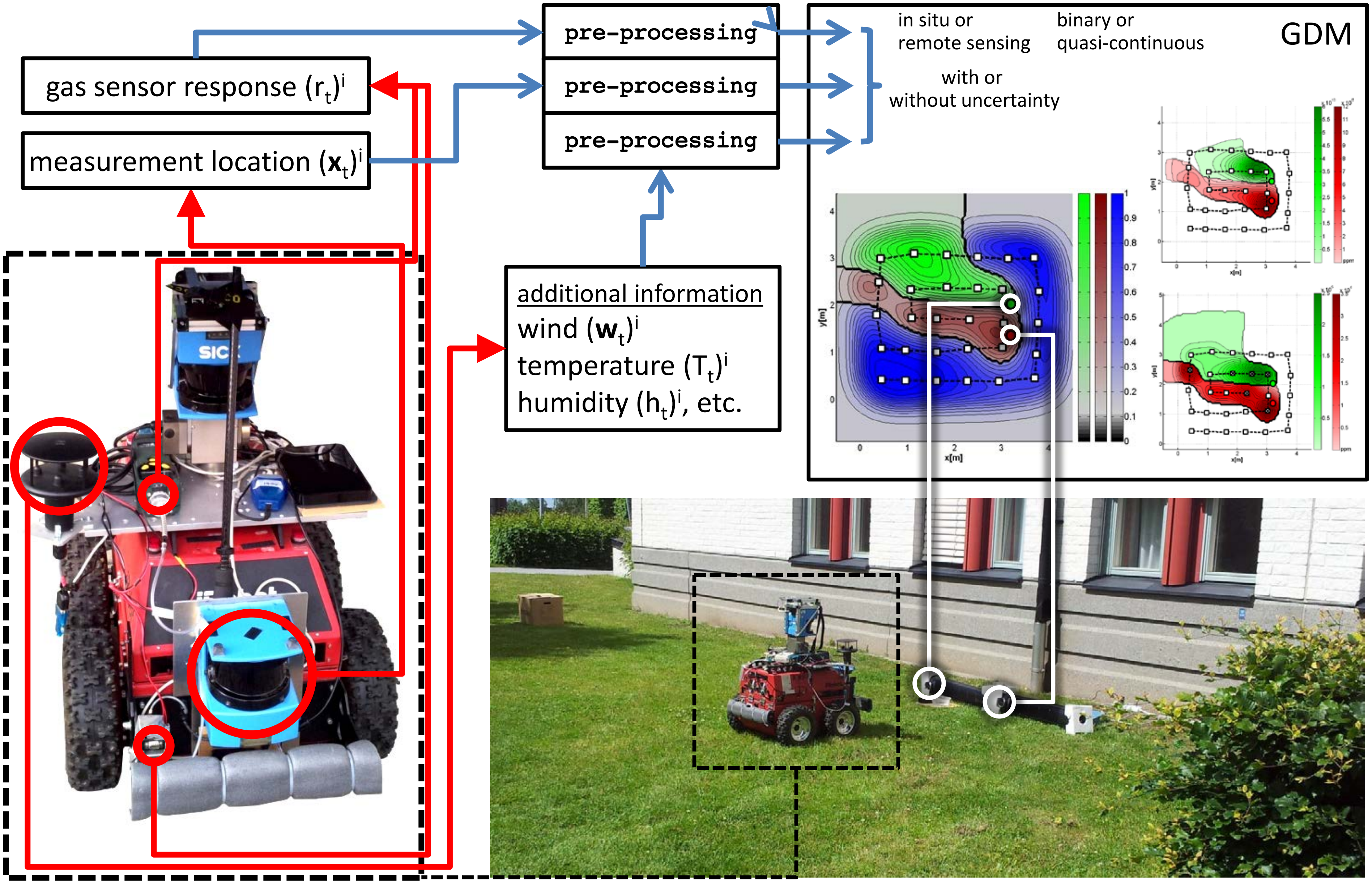


Components of MRO Systems – Example: Gas Distribution Mapping

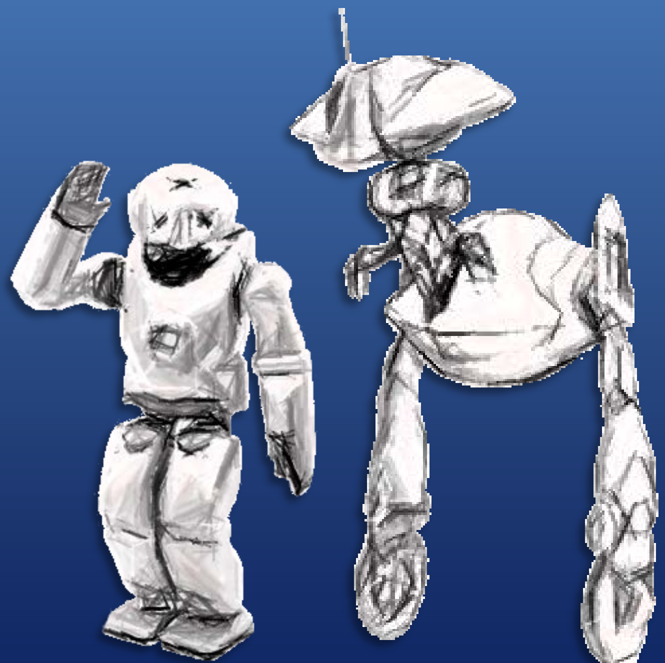


- **Advantages of Mobile Robot Environmental Monitoring?**

Advantages of Mobile Robot Environmental Monitoring?

- Higher spatial resolution
- Fewer sensors needed
- Mobility
- Adaptability
- Accurate Positioning
- Rapid deployment
- Can be exposed to dangerous environments
- Can carry out more than one task simultaneously

Why Do We Need Gas-Sensitive Robots?



- **Dedicated Gas-Sensitive Robots**
  - Search and Rescue (gas source localization, e.g. detecting leaks)

[Neumann et al., Energy Procedia 2013]

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2. Application Areas of Gas-Sensitive Mobile Robots

- **Dedicated Gas-Sensitive Robots**
  - Search and Rescue (gas source localization, e.g. detecting leaks)
  - Surveillance, Environmental Monitoring

[Hernandez Bennetts et al., ICRA 2013]
[Reggente et al., ChemEngTrans 2010]
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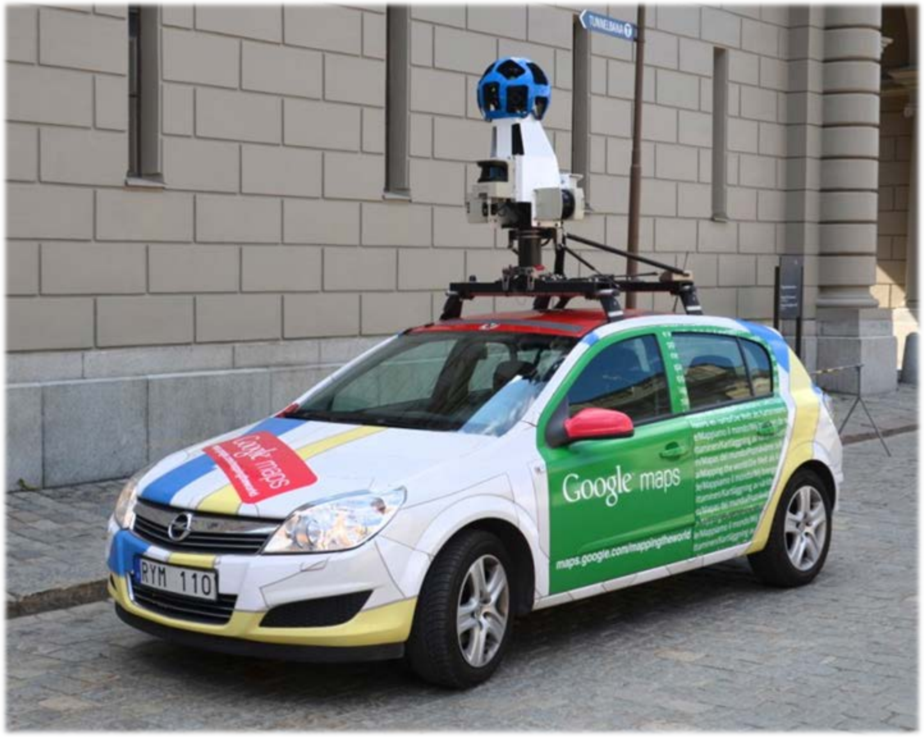

Environmental Defense Fund (EDF)
Colorado State University (CSU)
Google

http://www.edf.org/climate/methanemaps/partnership

The Gasbot Project

GASBOT

- **Monitoring of Landfill Sites 2011 – 2013**
  - **Objectives**

    Proof of concept (mobile robot for monitoring of Biogas emissions at landfill sites)

Atleverket

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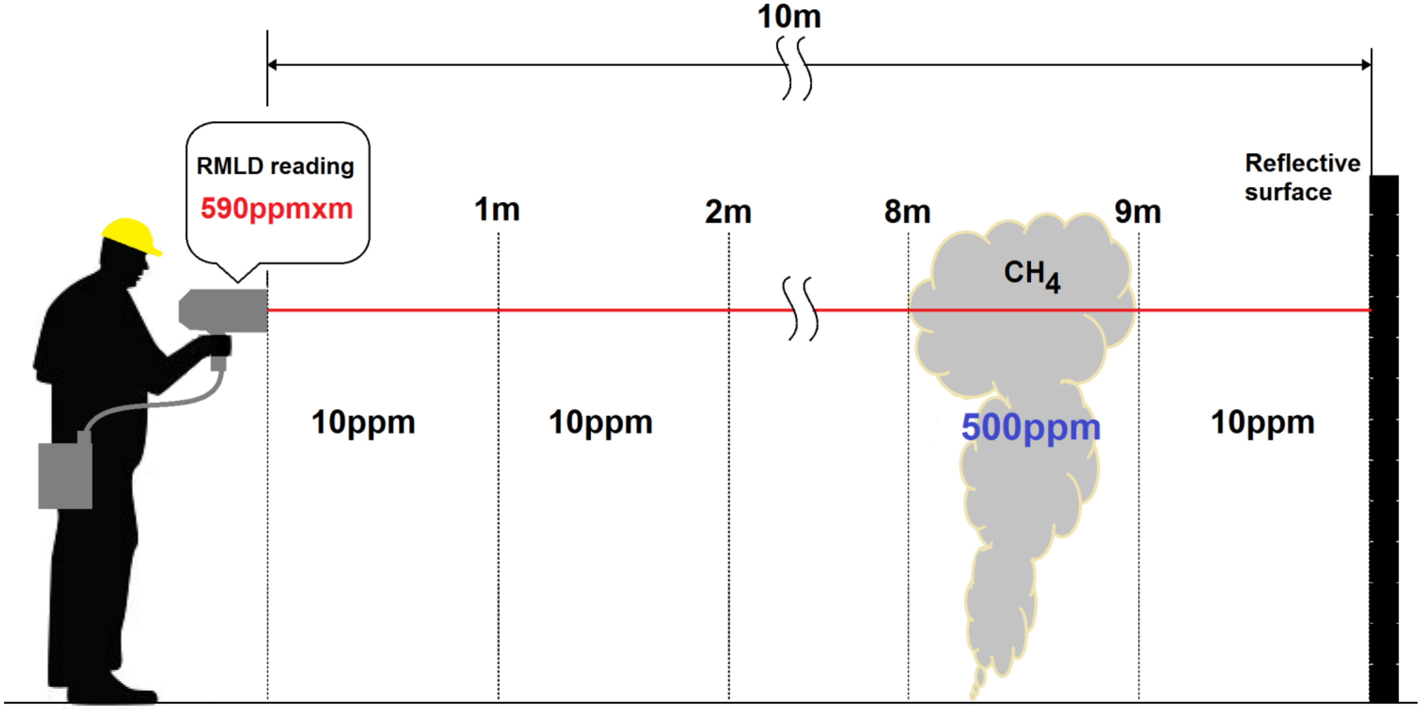
Decommissioned landfill site, Rynningeviken, Örebro

- **Monitoring of Landfill Sites** 2011 – 2013
  - **Objectives**
    Proof of concept (mobile robot for monitoring of Biogas emissions at landfill sites)
  - **Main Contribution**
    Gas distribution mapping with remote gas sensors



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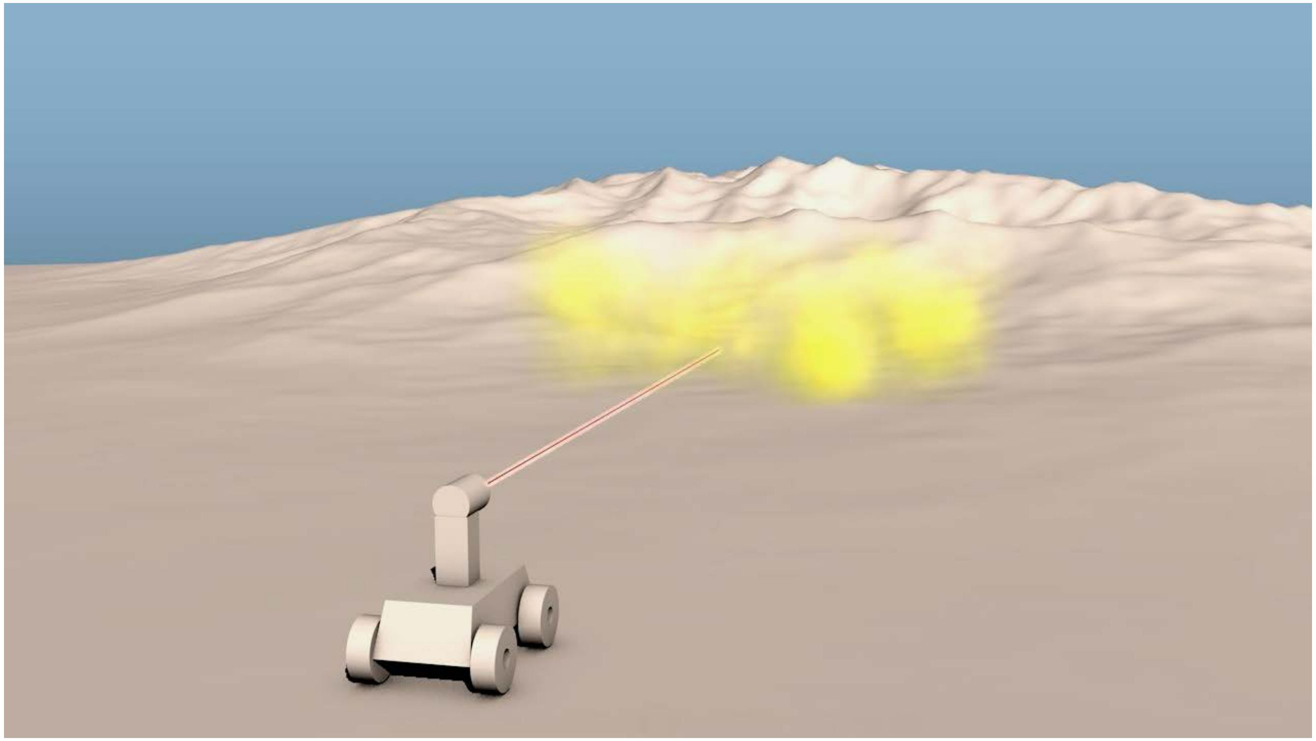

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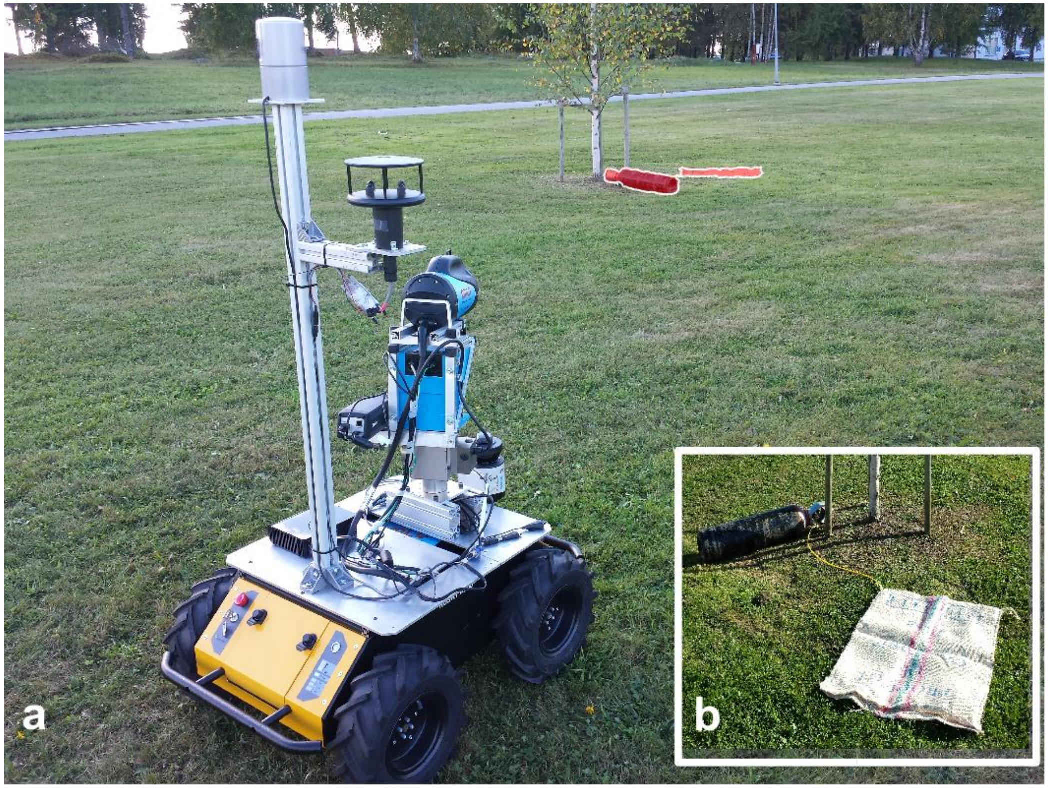

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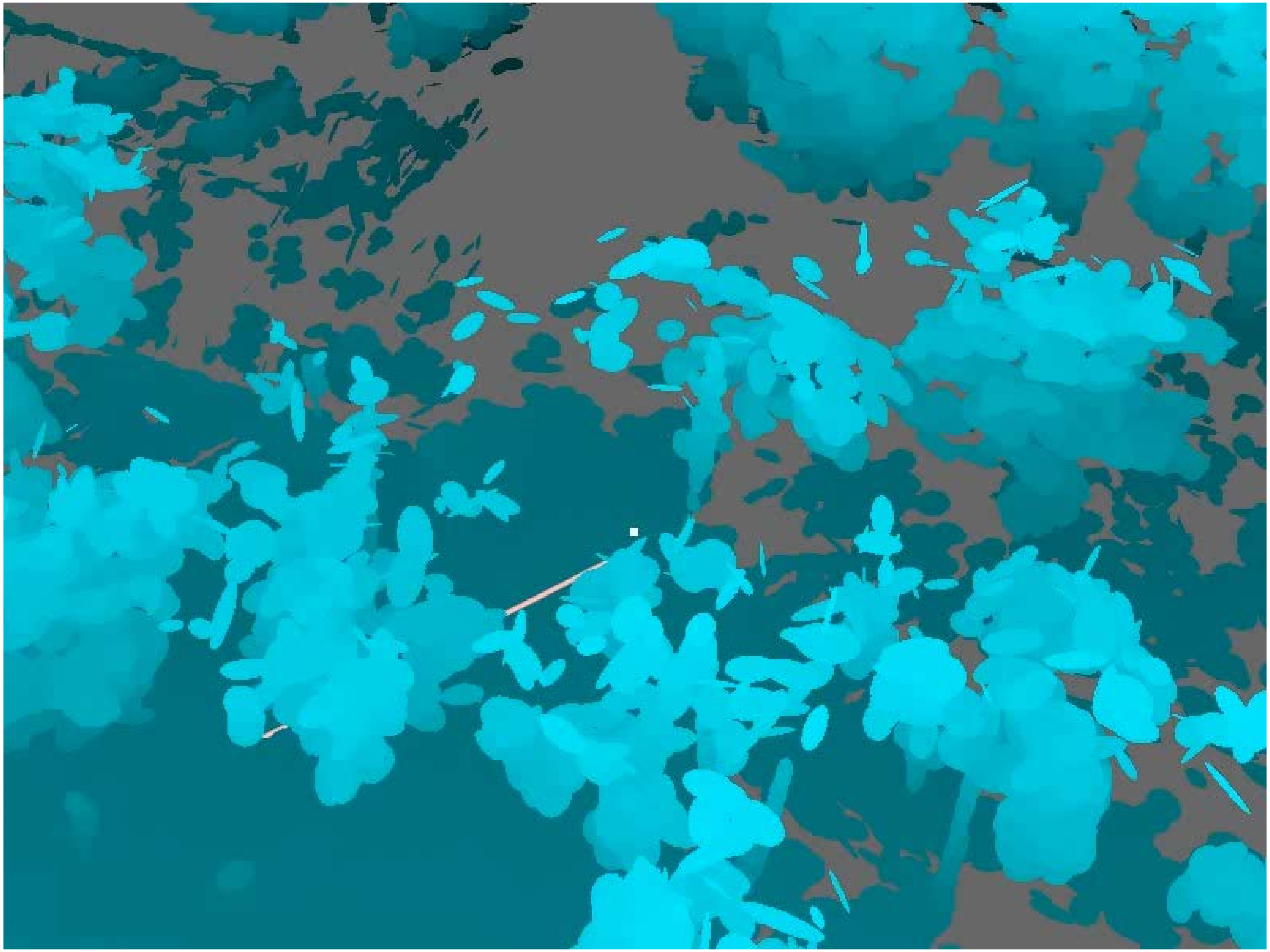

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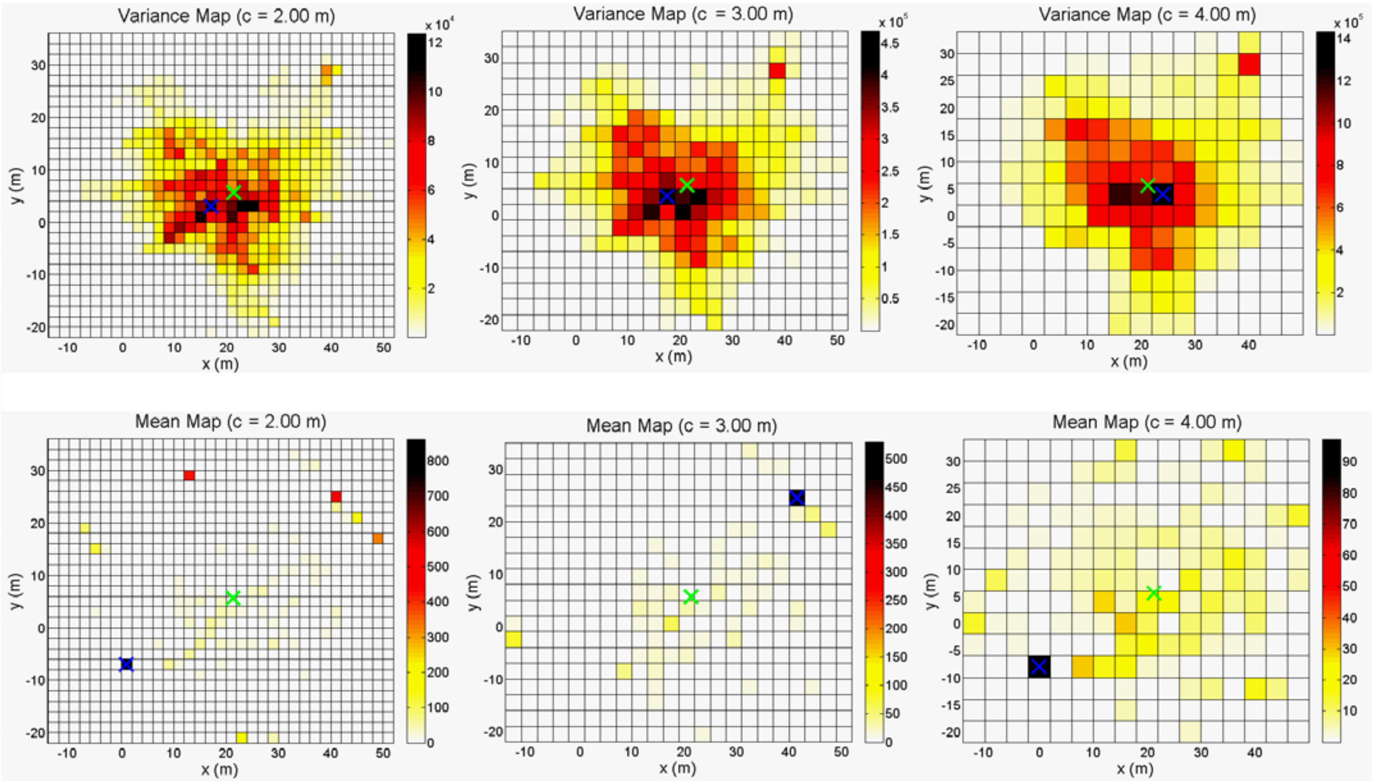

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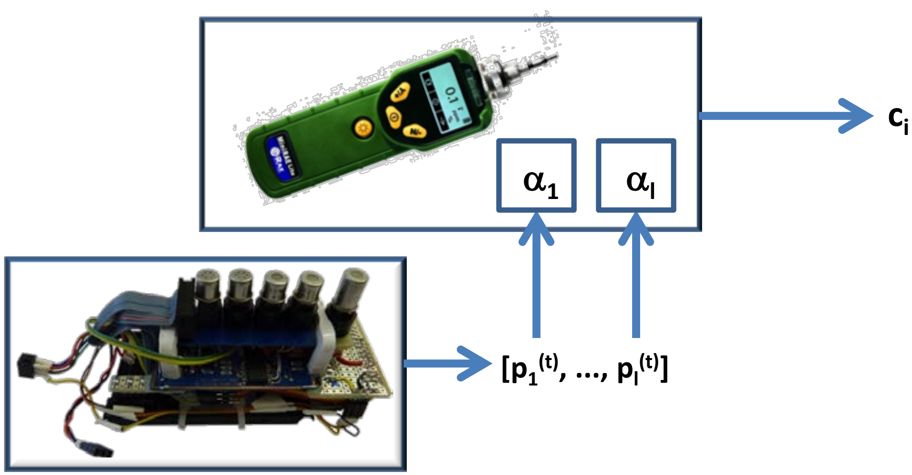
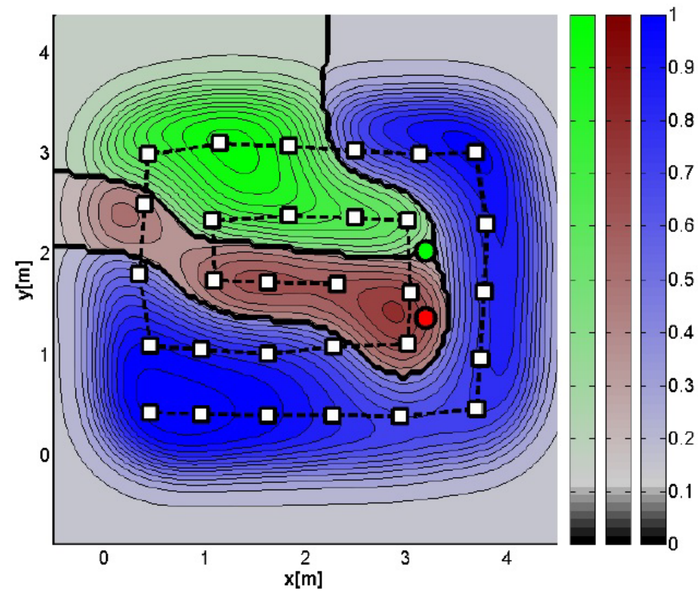
    Multi-component gas distribution mapping with *in situ* sensors





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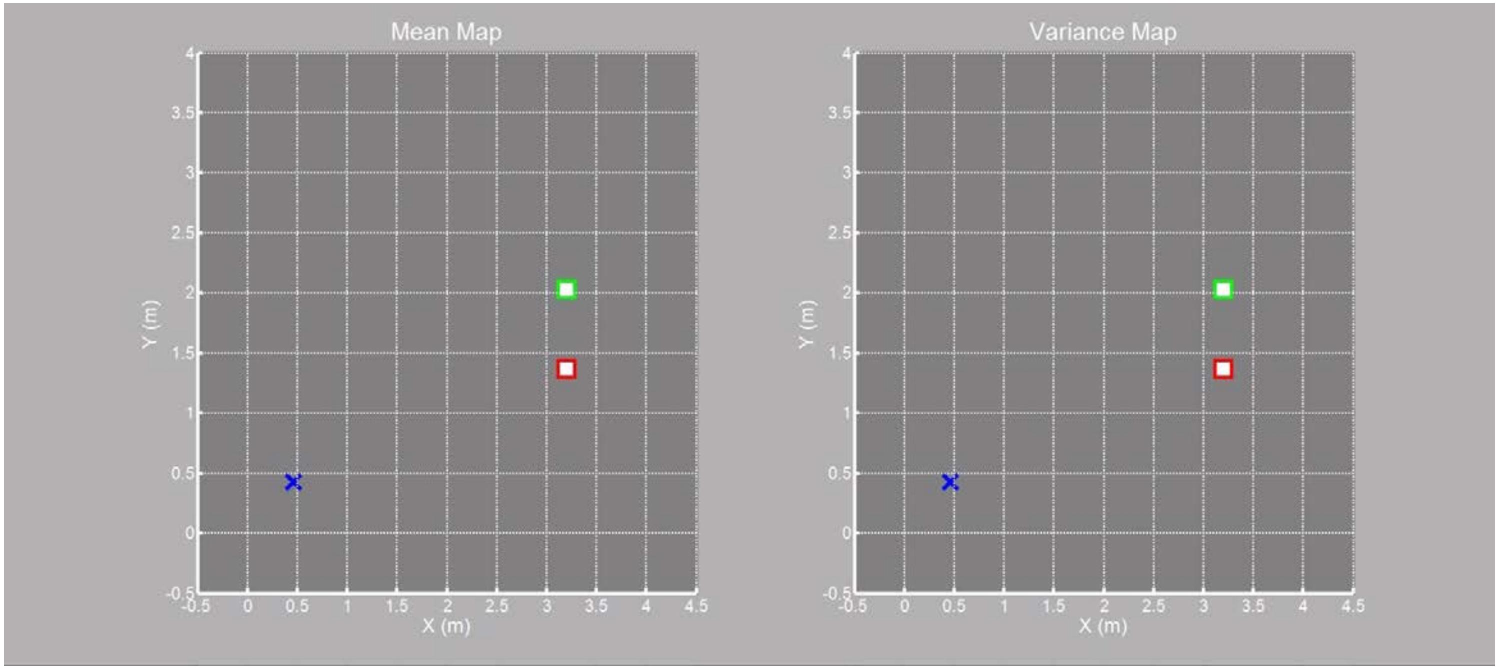

Monitoring of Landfill Sites 2011 – 2013

Objectives

Proof of concept (mobile robot for r
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Main Contribution

Gas distribution mapping with rem
Multi-component gas distribution n

Awards

- PartnerBot award for Environmental Co
- ICRA 2013: KUKA Best Service Robot Pa

Further Recognition

- Science Feb 2014 → IEEE Spectrum Apr 2014:
  Can Gasbots contribute
  to address the U.S. methane problem?

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White House Taps ARPA-E to Boost Methane Detection

By Peter Fairley
Posted 2 Apr 2014 | 21:50 GMT

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Victor Hernandez

In this month's issue of *IEEE Spectrum* we spotlight the methane emissions overlooked by the U.S. EPA's greenhouse gas inventory, and the

Gasbot

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    » The Gasbot Poem in Double Helix
      - Australian children's magazine published by the CSIRO (Australia's national science agency)

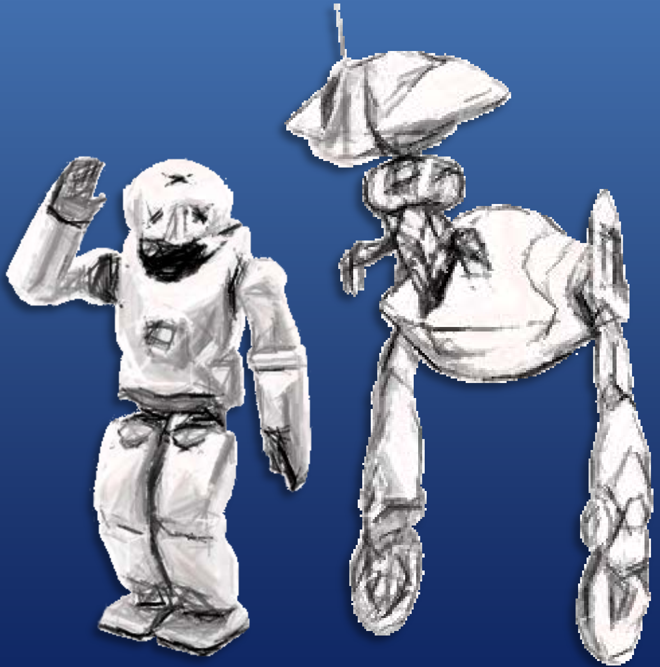
Let's call Gasbot

Stink-bomb bags
of kitchen waste
litter landfill's smelly place.
Rubbish mountains
by the load
are burping gases that explode.

Let's call Gasbot!
Methane chaser.
Sniffing air with zapping laser.
Shooting out
those beams of light
like Star Wars sabres in a fight.

Sensors on a
mobile robot
map out where the noxious gas got.
Let's call Gasbot!
Bots don't dread
to go where humans hate to tread.

Why Do We Need Gas-Sensitive Robots?



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[Hernandez Bennetts et al., ICRA 2013]
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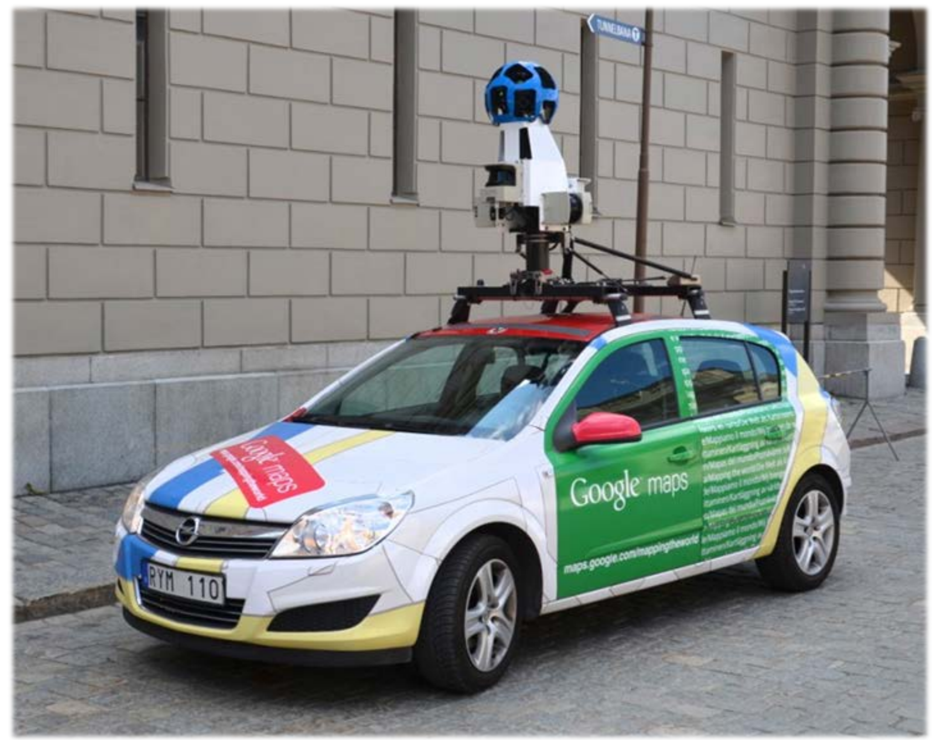

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- **Dedicated Gas-Sensitive Robots** [Hernandez Bennetts et al., IROS 2016]
  - o Search and Rescue (gas source localization, e.g. detecting leaks)
  - o Surveillance, Environmental Monitoring
    - » Robots as support and supplement for sensor networks
      - E.g.: KKS project RAISE

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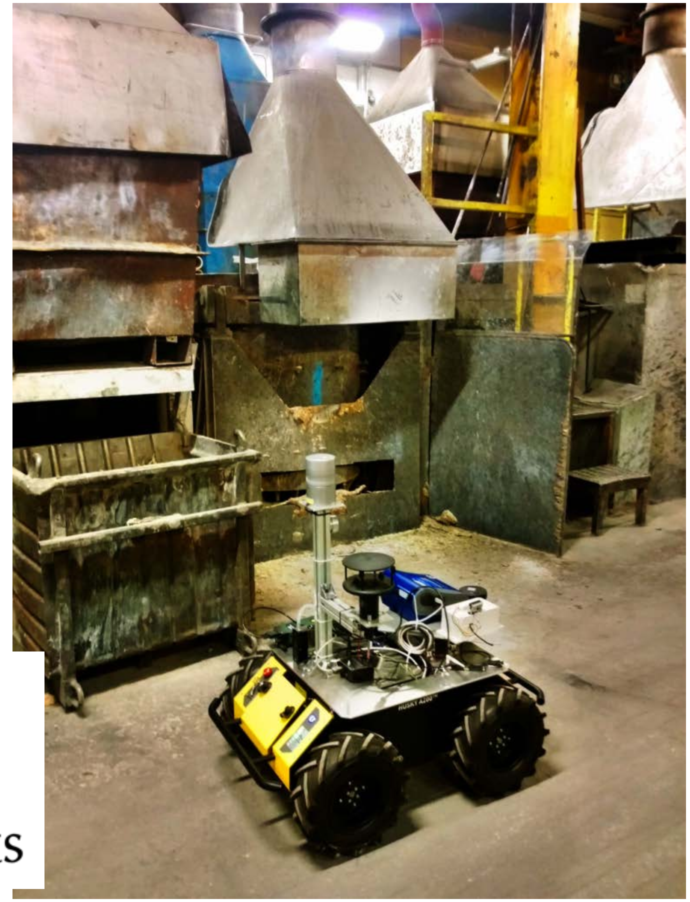
Global Castings
GULDSMEDSHYTTAN

JOHNSON METALL AB

RAISE
Robotic System for Air Quality Assessment in Industrial Environments



Dedicated Gas-Sensitive Robots

[Hernandez Bennetts et al., IROS 2016]

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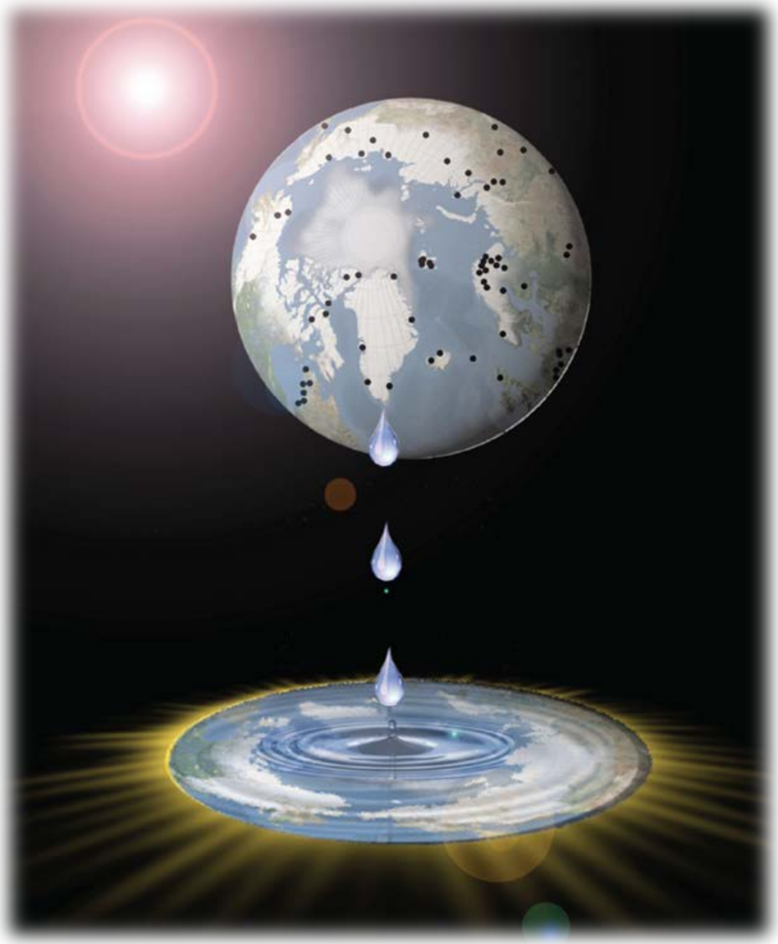
Global Castings
GULDSMEDSHYTTAN

JOHNSON METALL AB

RAISE Robotic System for Air Quality Assessment in Industrial Environments

More about RAISE later …

- **Dedicated Gas-Sensitive Robots**
  - o Search and Rescue (gas source localization, e.g. detecting leaks)
  - o Surveillance, Environmental Monitoring
  - o Scientific missions (climate research)



Gas Sensing as Addition to Available Robots

- Detect leaking gas pipes
- Detect fire at its initial stage (CO)

Application Areas of Gas-Sensitive Mobile Robots

- **Gas Sensing as Addition to Available Robots**
  - Detect leaking gas pipes
  - Detect fire at its initial stage
  - Monitor pollutants in the environment (e.g.: Dustbot)

[Reggente et al., ChemEngTrans 2010]

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In Computer Science synapsis eHealth Networks

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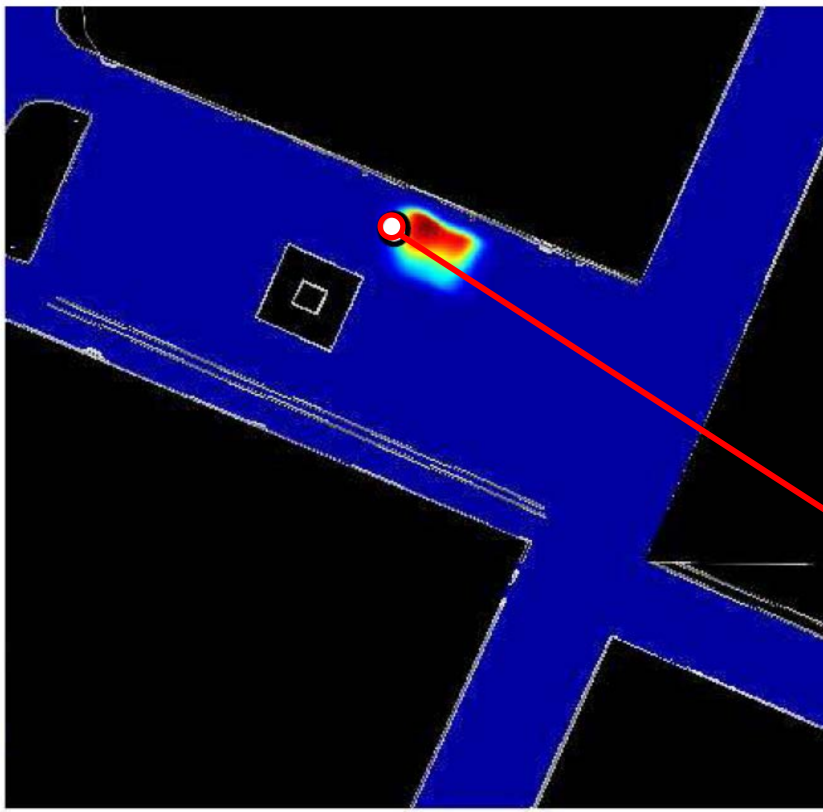
- **Gas Sensing as Addition to Available Robots**
  - EU FP6 Project DustBot ("Robots for Urban Hygiene")
    - E.g.: outdoor pollution monitoring experiments

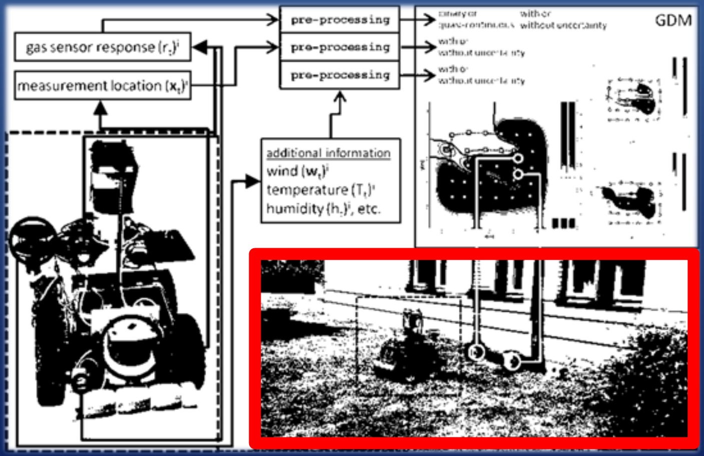
[Reggente et al., ChemEngTrans 2010]



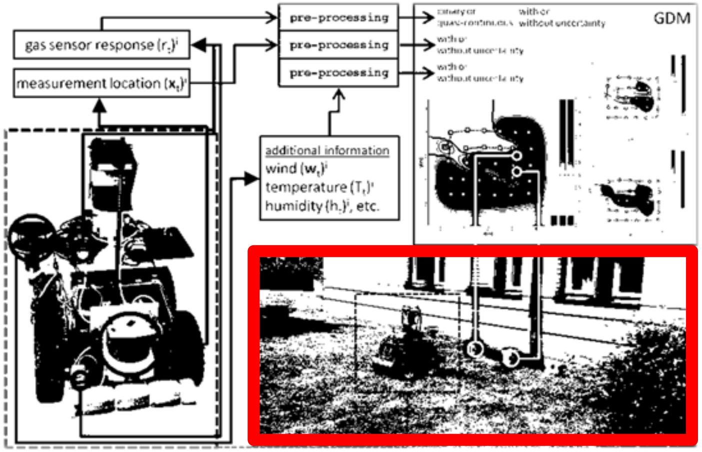
Mobile Robot Olfaction is hard!

Gas Dispersal

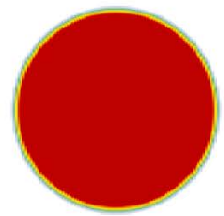
in Natural Environments



- **Turbulent Gas Dispersal**



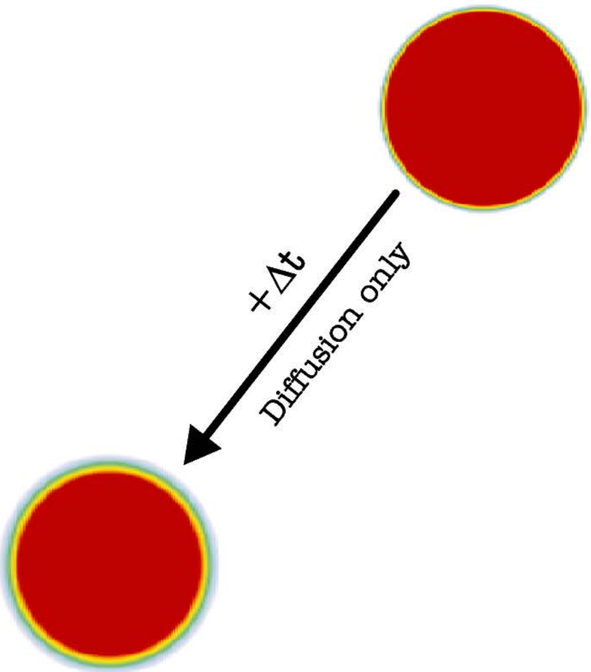
- **Turbulent Gas Dispersal**
  - Diffusion



[Smyth and Moum, 2001]
[Roberts/Webster, 2000]

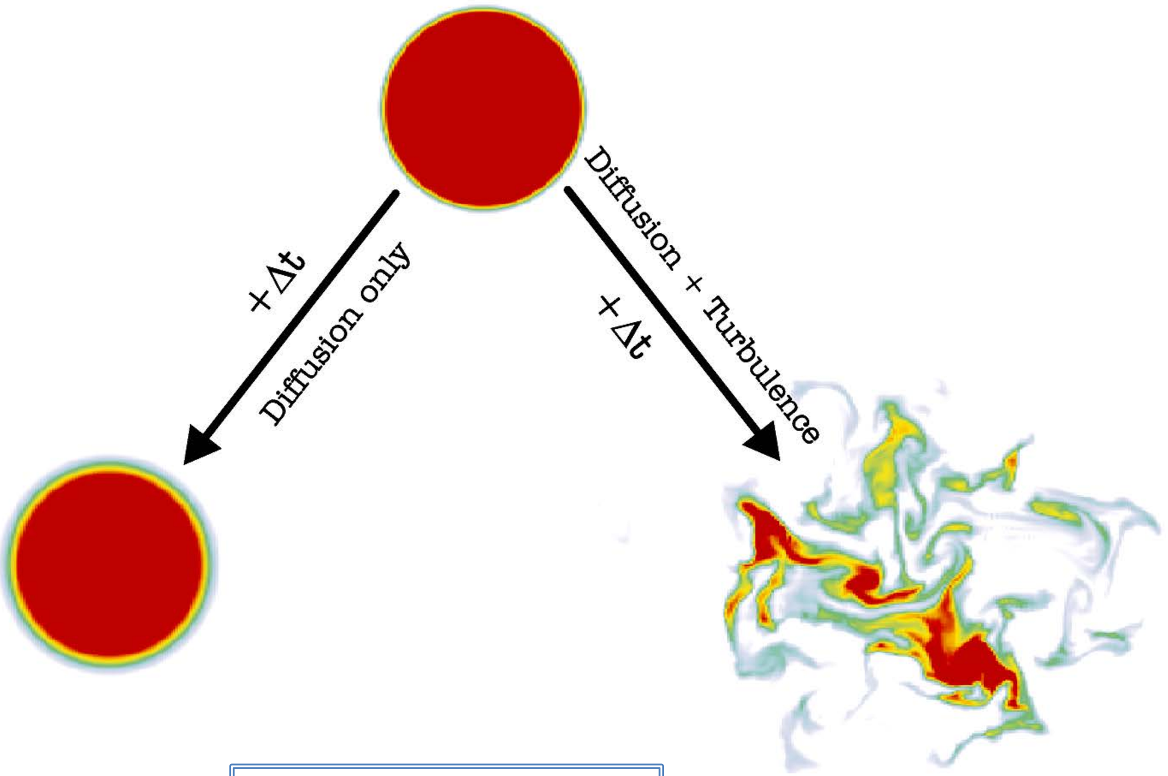
Turbulent Gas Dispersal

- Diffusion



[Smyth and Moum, 2001]
[Roberts/Webster, 2000]

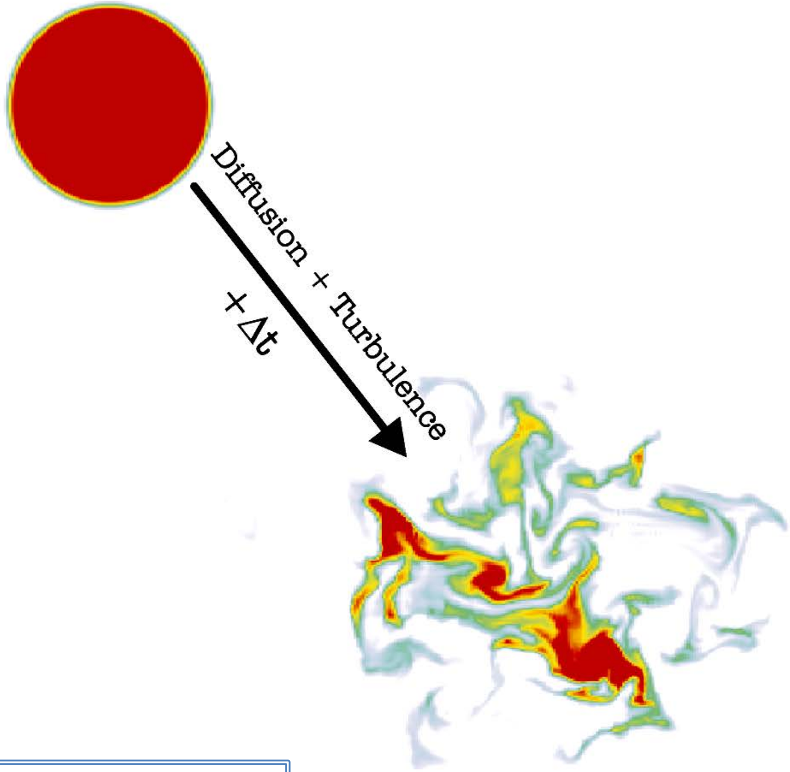
- **Turbulent Gas Dispersal**
  - Diffusion
  - Advective transport
  - Turbulent transport



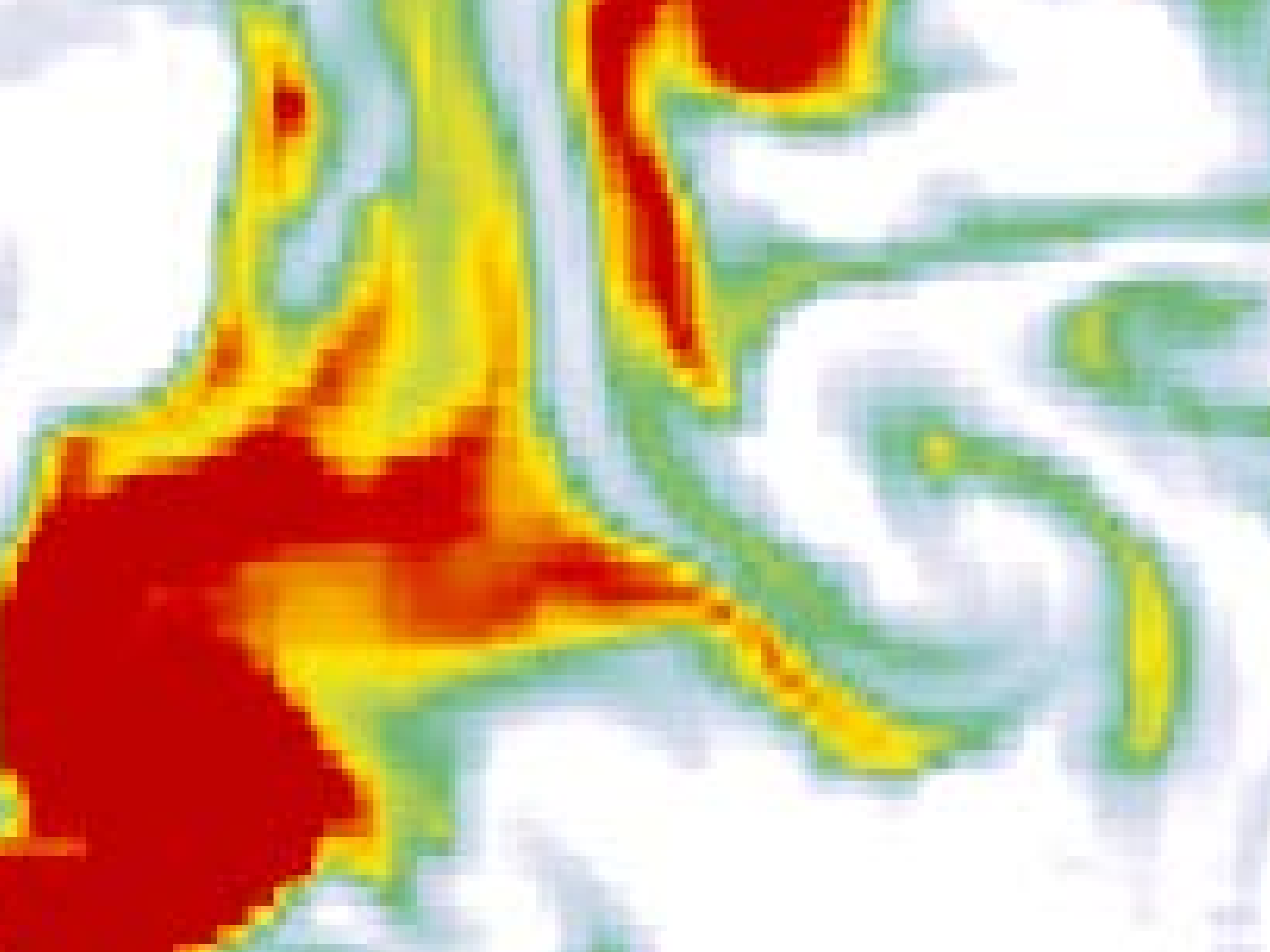
[Smyth and Moum, 2001]
[Roberts/Webster, 2000]

Turbulent Gas Dispersal

- ~~Diffusion~~
- Advective transport
- Turbulent transport

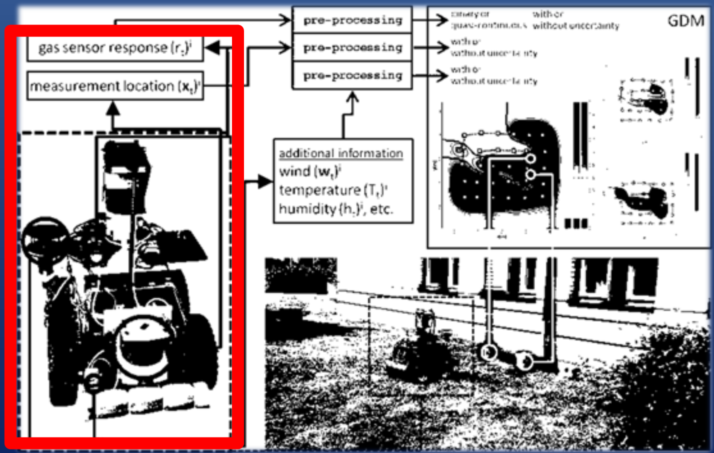


[Smyth and Moum, 2001]
[Roberts/Webster, 2000]

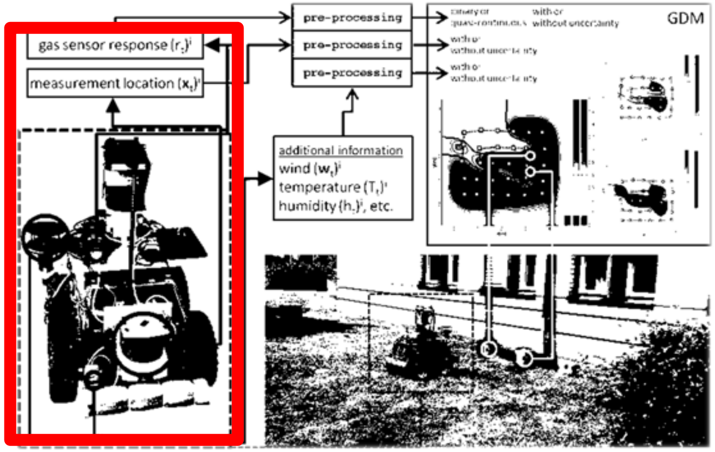


Mobile Robot Olfaction is hard!

Remote and In Situ Gas Sensing



- **Further Challenges, General**



- **Further Challenges, General**
  - Space, power, weight, time restrictions
  - Varying environmental conditions (temperature, humidity, …)

? →

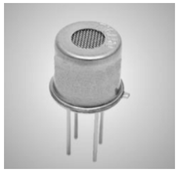
Further Challenges, In Situ Sensing

- Need direct contact with the gas patches
- Report point concentration measurements
- Prices in the range of 10€ to 70,000€

Further Challenges, In Situ Sensing – MOX Gas Sensors

- By far the most widely used gas sensing technology in MRO
- Advantages
  - Commercially available
  - Relatively fast response
  - High sensitivity to substances of interest
  - Light (few grams)
  - Simple electronic to interface

e2v
Mics 5121



Figaro
TGS 2620

▪ Further Challenges, In Situ Sensing – MOX Gas Sensors

- By far the most widely used gas sensing technology in MRO
- Advantages
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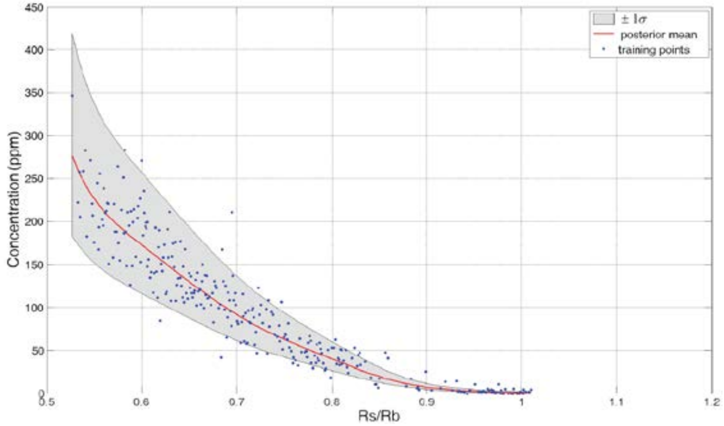
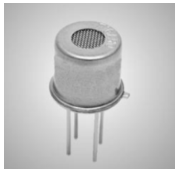
  - Relatively fast response
  - High sensitivity to substances of interest
  - Light (few grams)
  - Simple electronic to interface
- Disadvantages
  - Non calibrated readings



e2v
Mics 5121



Figaro
TGS 2620

- **Further Challenges, In Situ Sensing – MOX Gas Sensors**
  - By far the most widely used gas sensing technology in MRO
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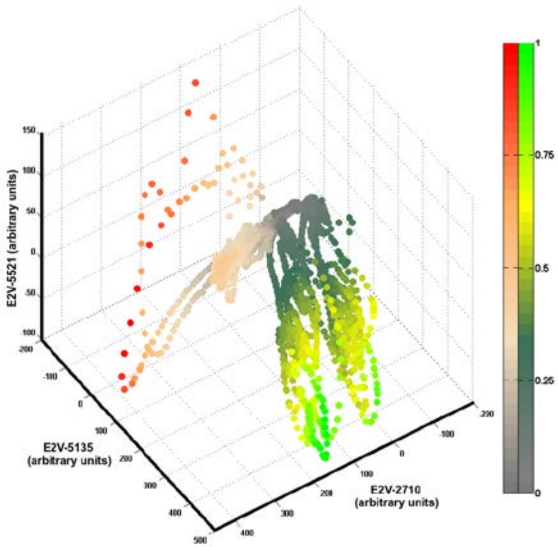
    - High sensitivity to substances of interest
    - Light (few grams)
    - Simple electronic to interface
  - Disadvantages
    - Non calibrated readings
    - Partially selective



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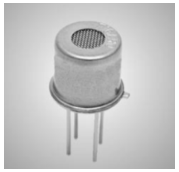
Mics 5121



Figaro
TGS 2620

Further Challenges, In Situ Sensing – MOX Gas Sensors

- By far the most widely used gas sensing technology in MRO
- Advantages
  - Commercially available
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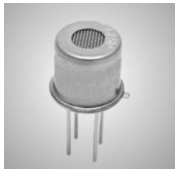
- Disadvantages
  - Non calibrated readings
  - Partially selective
  - Point measurement (no long-range measurements like e.g. laser scanners or cameras)

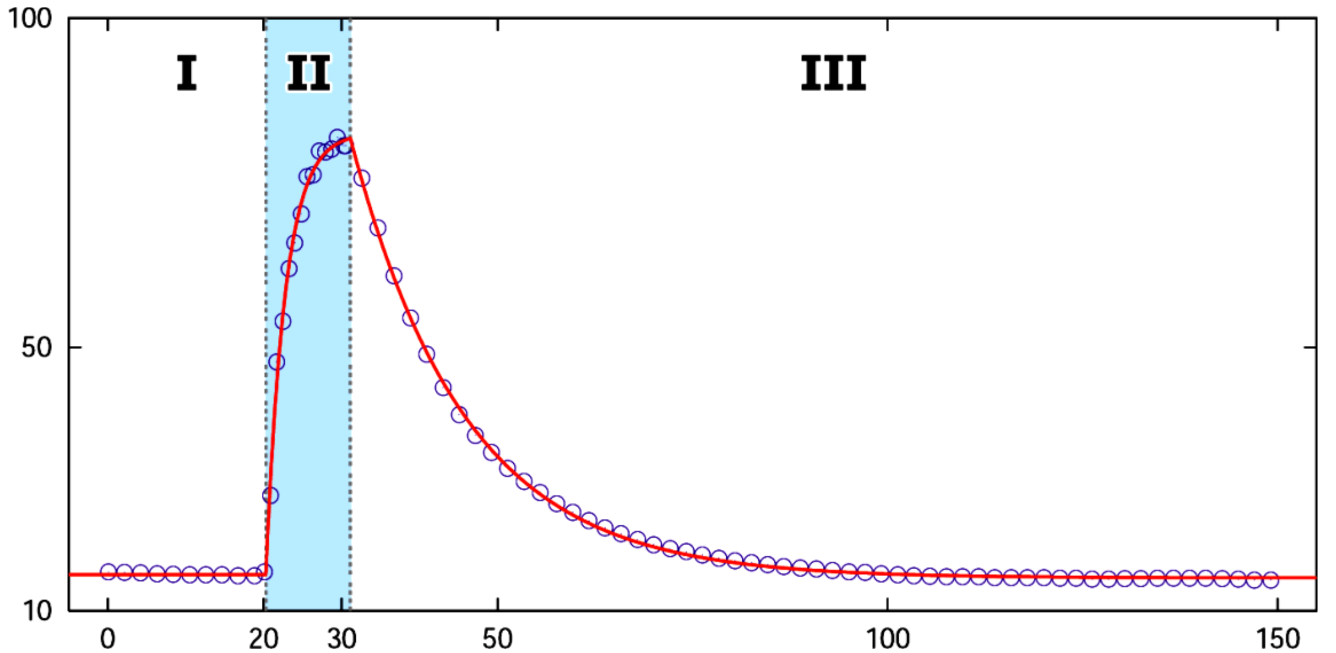
e2v
Mics 5121



Figaro
TGS 2620

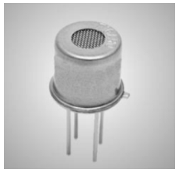
Further Challenges, In Situ Sensing – MOX Gas Sensors

- By far the most w
- Advantages
  - Commercially ava
  - Relatively fast res
  - High sensitivity tc
  - Light (few grams)
  - Simple electronic



- Disadvantages
  - Non calibrated re
  - Partially selective
  - Point measurement (no long-range measurements like e.g. laser scanners or cameras)
  - Slow sensor dynamics (long response time, very long recovery time)

e2v
Mics 5121

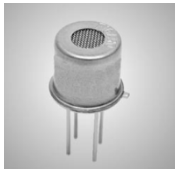


Figaro
TGS 2620

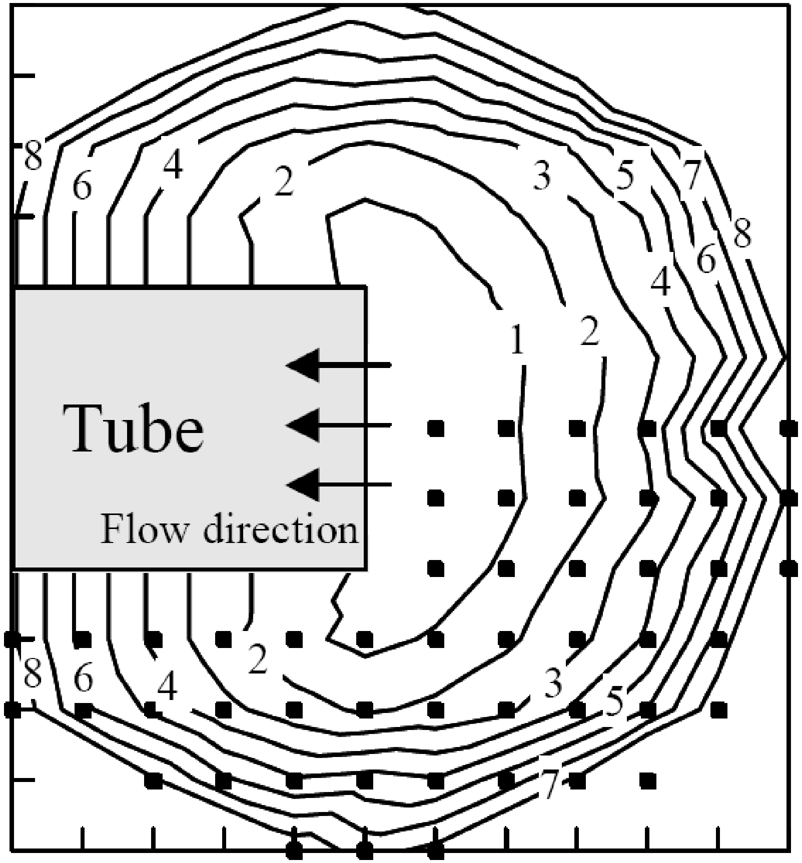
Further Challenges, In Situ Sensing

- Point measurement ⇔ sparse sampling
  - Sensitive sensor surface is typically small (often < $1cm^2$)
  - Effective sampling region is also small

e2v
Mics 5121



Figaro
TGS 2620



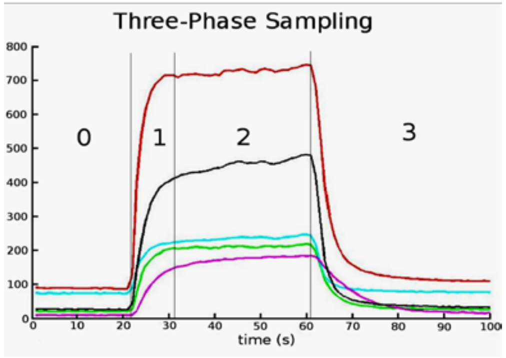
- **Further Challenges, In Situ Sensing**
  - Point measurement ⬄ sparse sampling
  - Open sampling system
    - Direct exposition of gas sensors to the environment
    - Gas sampling from uncontrolled environment
    - Typically continuous sampling

? →

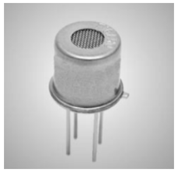
Further Challenges, In Situ Sensing – MOX Gas Sensors

- Point measurement ⇔ sparse sampling
- Open sampling system + sensor dynamics + turbulent gas dispersal
  - Steady state response never reached

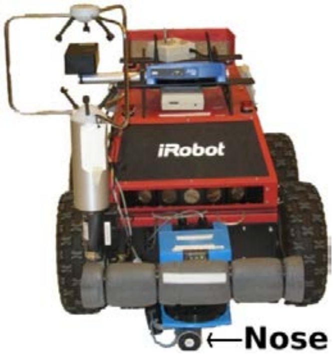
Traditional three-phase sampling



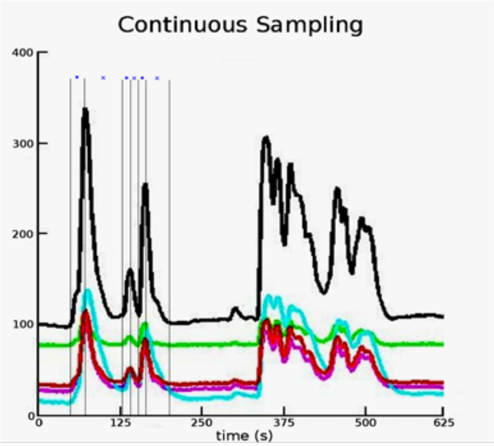
e2v
Mics 5121



Figaro
TGS 2620

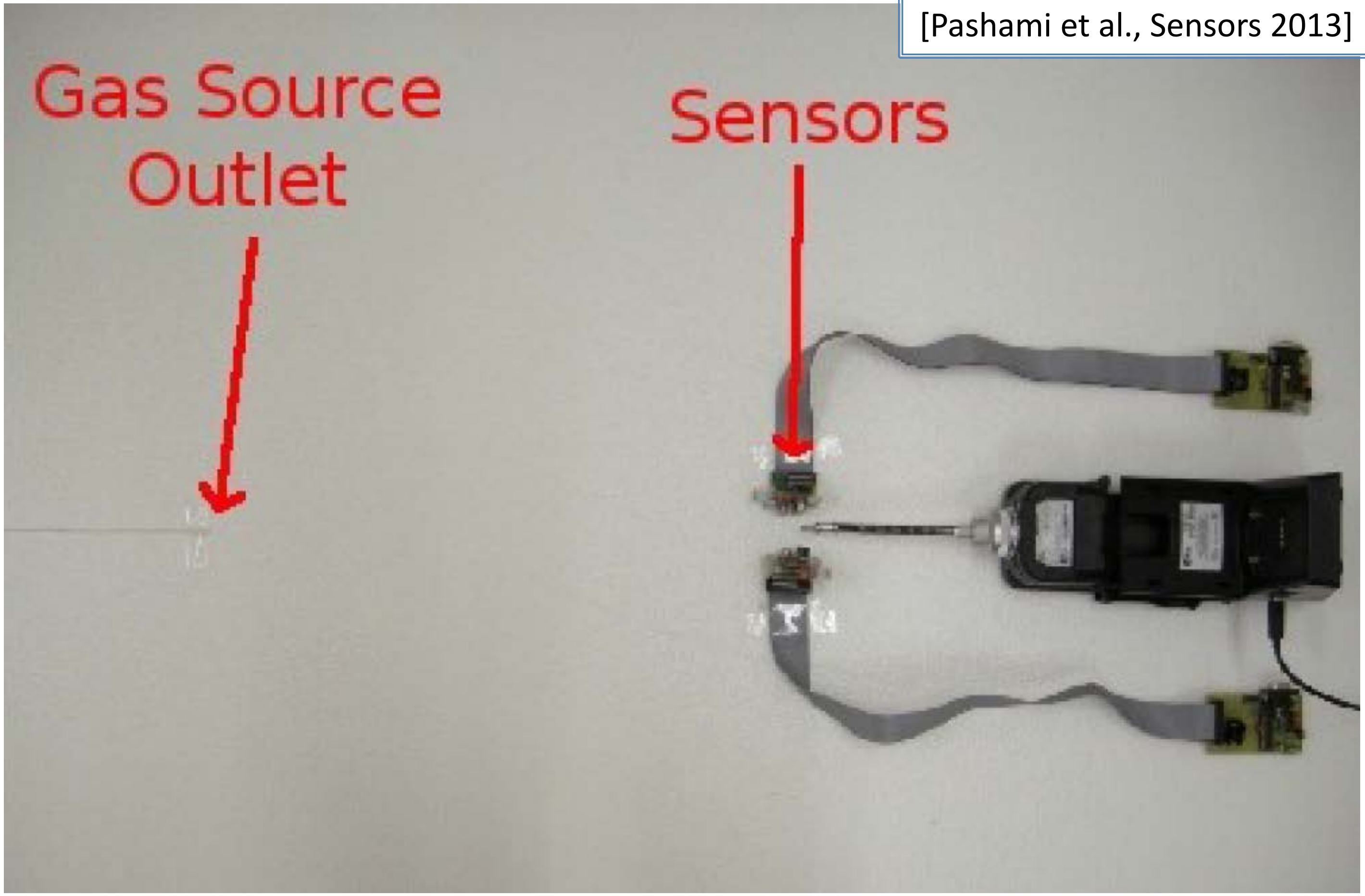


Continuous (open) sampling with a mobile robot



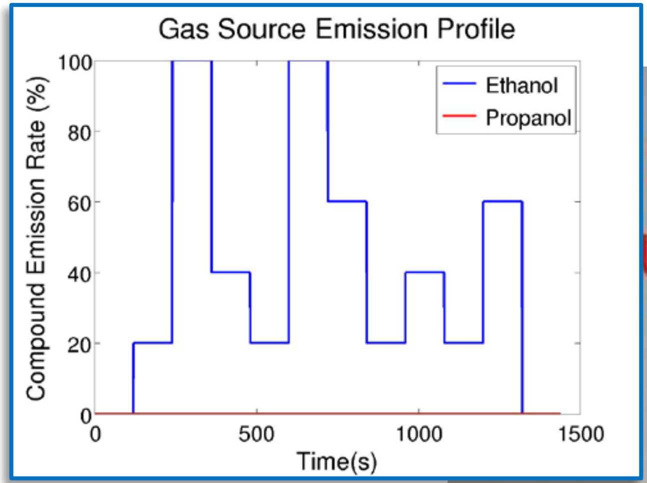
- **Further Challenges, In Situ Sensing – MOX Gas Sensors**
  - Open sampling system + sensor dynamics + turbulent gas dispersal

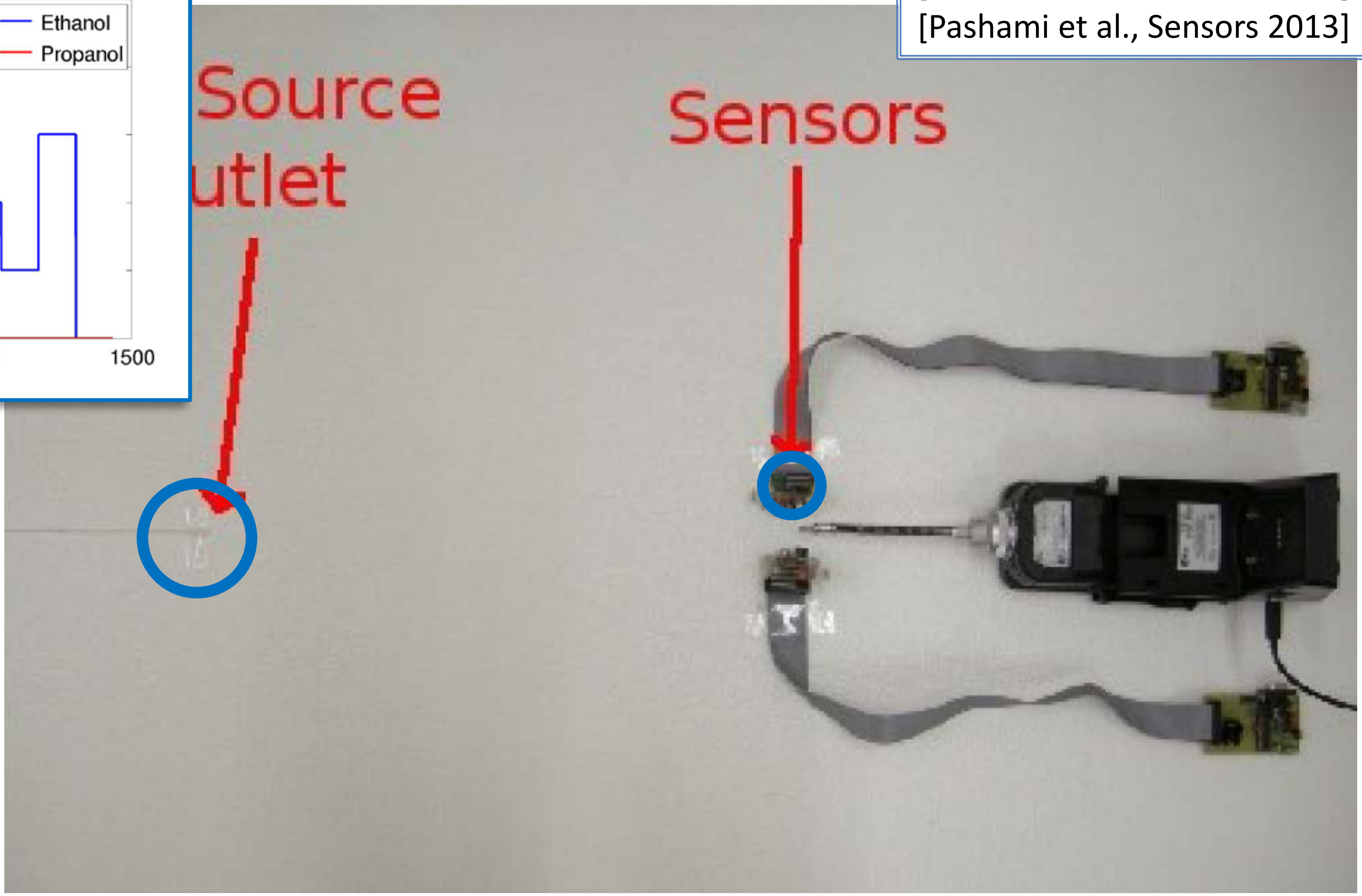
[Pashami et al., Sensors 2012]
[Pashami et al., Sensors 2013]



Data collected by Yuichiro Fukazawa, Marco Trincavelli, Yuta Wada and Hiroshi Ishida

Further Challenges, In Situ Sensing – MOX Gas Sensors

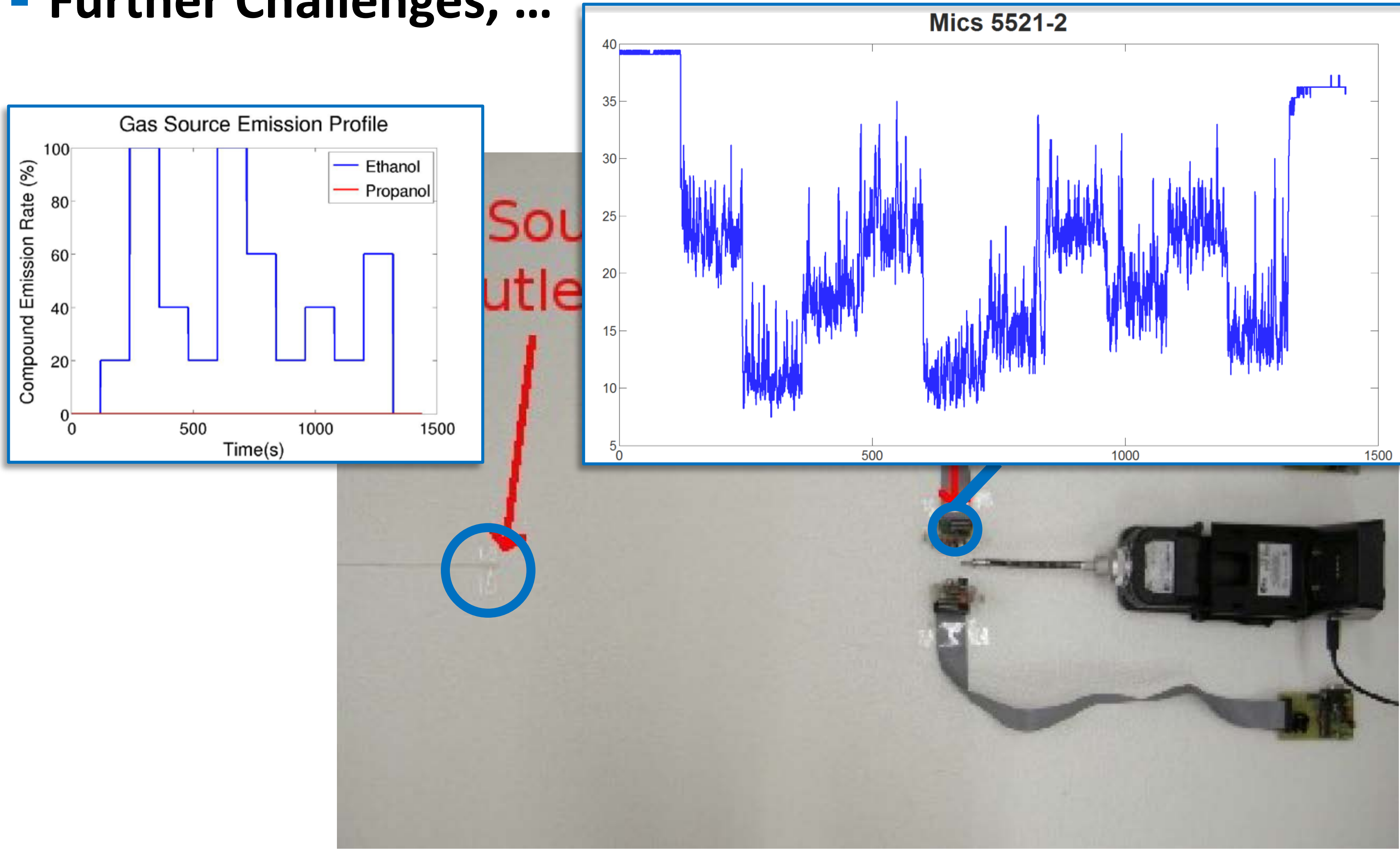




[Pashami et al., Sensors 2012]
[Pashami et al., Sensors 2013]

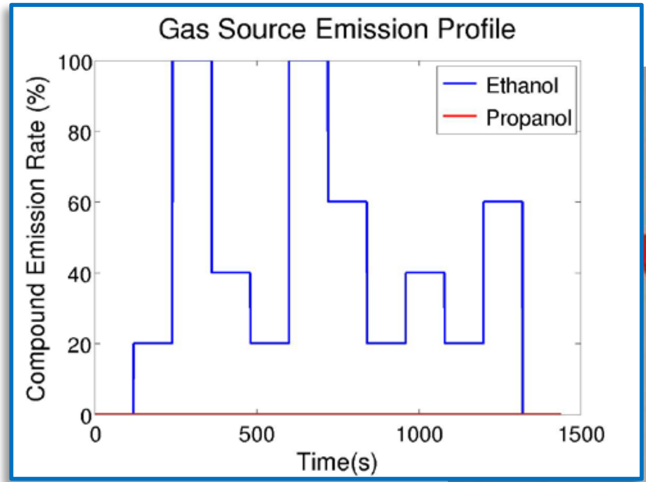
Data collected by Yuichiro Fukazawa, Marco Trincavelli, Yuta Wada and Hiroshi Ishida

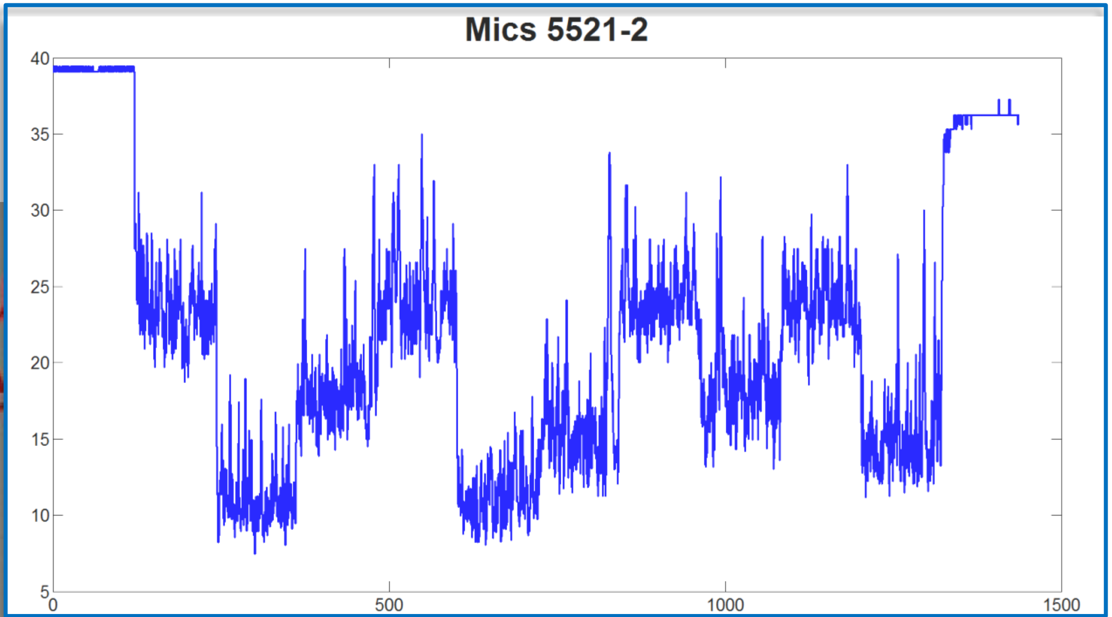
- # Further Challenges, …

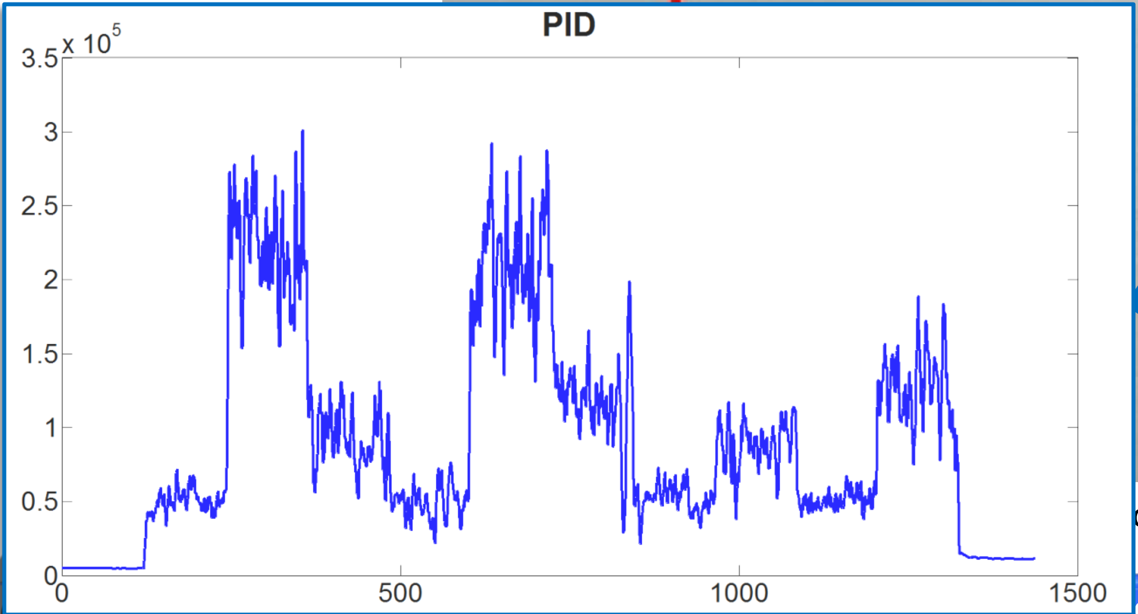


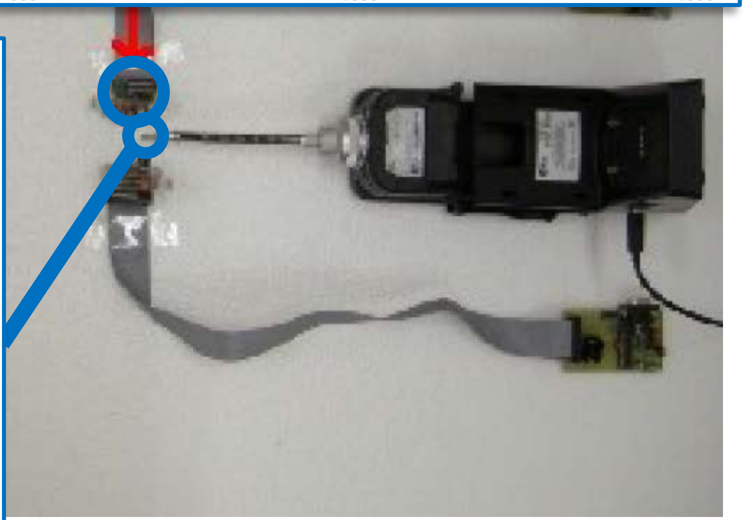
Data collected by Yuichiro Fukazawa, Marco Trincavelli, Yuta Wada and Hiroshi Ishida

Further Challenges, …



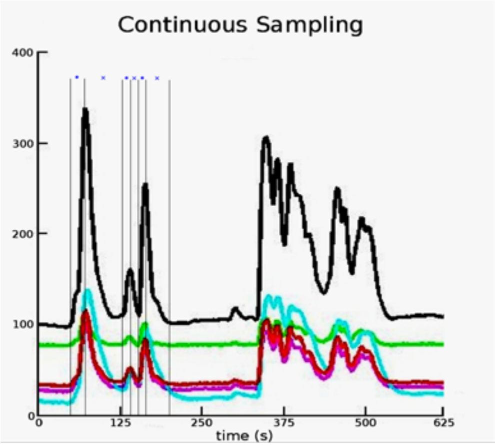






co Trincavelli, Yuta Wada and Hiroshi Ishida

- **Further Challenges, In Situ Sensing – MOX Gas Sensors**
  - Point measurement ⇔ sparse sampling
  - Open sampling system + sensor dynamics + turbulent gas dispersal
    - Steady state response never reached
  - Calibration
    - Complicated "sensor response ⇔ concentration" relation
    - Has to consider sensor dynamics



- **Further Challenges, In Situ Sensing – MOX Gas Sensors**
  - Point measurement ⇔ sparse sampling
  - Open sampling system + sensor dynamics + turbulent gas dispersal
    - Steady state response never reached
  - Calibration
    - Complicated "sensor response ⇔ concentration" relation
    - Has to consider sensor dynamics
    - Dependent on other variables (temperature, humidity, ...)
    - Variation between individual sensors
    - Long-term drift

- **Further Challenges, General**
  - Space, power, weight restrictions
  - Varying environmental conditions (temperature, humidity, …)
- **Further Challenges, In Situ Sensing**
  - Open sampling system
    - Direct exposition of gas sensors to the environment
    - Less controlled gas sampling
    - Typically continuous sampling
  - Point measurement
  - Sensor dynamics (response/recovery time)
  - Calibration
- **Further Challenges, Remote Sensing**
  - Integral measurements / dynamic environment

Not mentioned in the presentation

- **Further Challenges, General**
  - Space, power, weight restrictions
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- **Further Challenges, In Situ Sensing**
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    - Typically continuous sampling
  - Point measurement

    Sec. 4, ~~5,~~ 7: What's In-Between?
  - Sensor dynamics (response/recovery time)
  - Calibration
- **Further Challenges, Remote Sensing**
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- **Further Challenges, General**
  - Space, power, weight restrictions
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- **Further Challenges, In Situ Sensing**
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    - Typically continuous sampling
  - Point measurement

    Sec. 4, ~~5,~~ 7: What's In-Between?
  - Sensor dynamics (response/recovery time)
  - Calibration
- **Further Challenges, Remote Sensing**
  - Integral measurements / dynamic environment

    ~~Sec. 6: Gas Tomography~~

GDM with In Situ Sensors

Statistical GDM:

Problem Statement

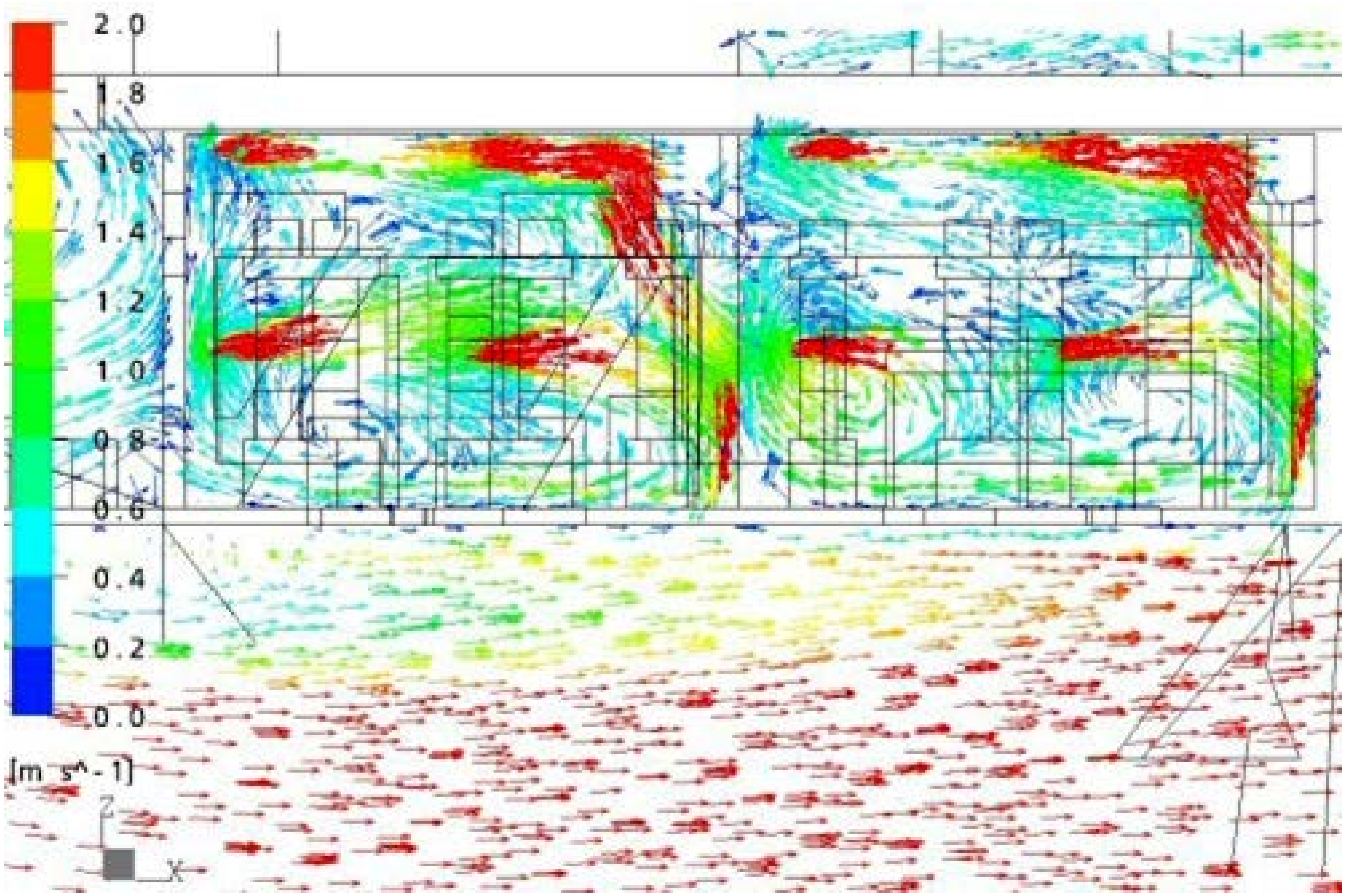
$$p\left(r_* \mid \vec{x}_*, \vec{x}_{1:n}, r_{1:n}\right)$$

$$p\left(\mathbf{m} \mid \vec{x}_{1:n}, r_{1:n}\right)$$

- **Computation of Turbulent Gas Distribution?**

[Google Image Search, 1st hit for "office", http://hof.povray.org/images/800x600/office-13.jpg]

- **Simulation of Turbulent Gas Distribution?**
  - Computational fluid Dynamics (CFD) models?



Computation of Turbulent Gas Distribution?

- No general solution to the fluid dynamics equations
- Numerical simulations computationally expensive and depend sensitively on the initial/boundary conditions
- Initial/boundary conditions not known in typical scenarios

⇒ Model gas distribution statistically from a large number of measurements

- **Statistical Gas Distribution Modelling**

[Lilienthal et al., ECMR 2007]

  - Interpret gas sensor measurements statistically
    - » Statistical representation
      - Gas sensor measurements treated as random variables
    - » Build a representation of the observed gas distribution from a sequence of measurements

[Lilienthal et al., ECMR 2007]

- **Statistical Gas Distribution Modelling**
  - Interpret gas sensor measurements statistically
    - Statistical representation
      - Gas sensor measurements treated as random variables
    - Build a representation of the observed gas distribution from a sequence of measurements
- **Problem Definition: Stat. Gas Distribution Modelling**
  - Learn predictive model

$$p\left(r_* \mid \vec{x}_*, \vec{x}_{1:n}, r_{1:n}\right)$$

gas measurements

gas prediction

query location

measurement locations

- **Statistical Gas Distribution Modelling**

[Lilienthal et al., ISOEN 2009]

  - Interpret gas sensor measurements statistically
    - Statistical representation
      - Gas sensor measurements treated as random variables
    - Build a representation of the observed gas distribution from a sequence of measurements
  - Good model?

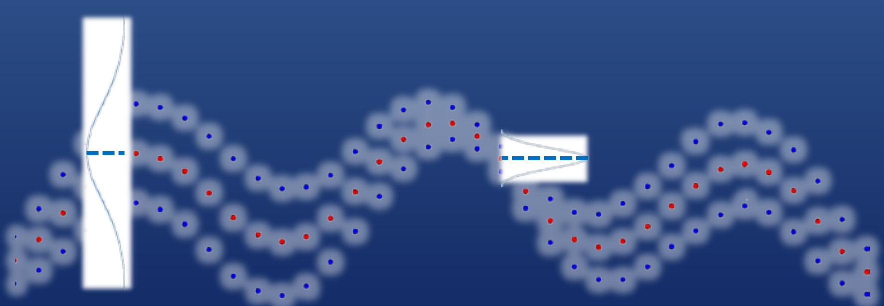
Statistical Gas Distribution Modelling

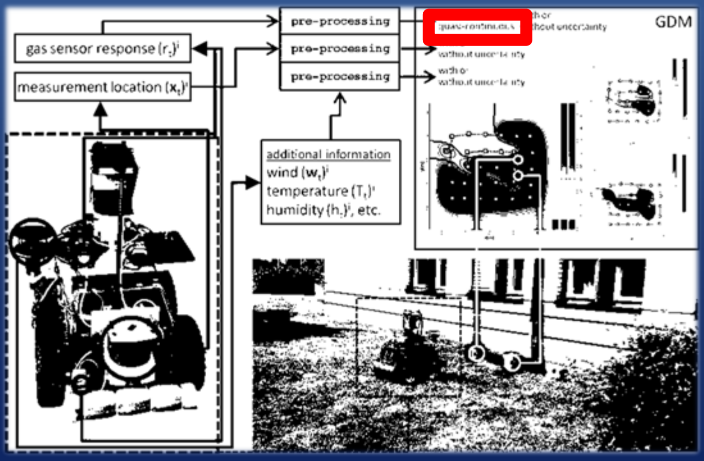
[Lilienthal et al., ISOEN 2009]

- Interpret gas sensor measurements statistically
  - Statistical representation
    - Gas sensor measurements treated as random variables
  - Build a representation of the observed gas distribution from a sequence of measurements
- Good model?
  - Allows to infer concentration levels
    "explains observations and accurately predict new ones"
  - Allows to infer hidden parameters
    - Average concentration
    - Gas source location

GDM with In Situ Sensors

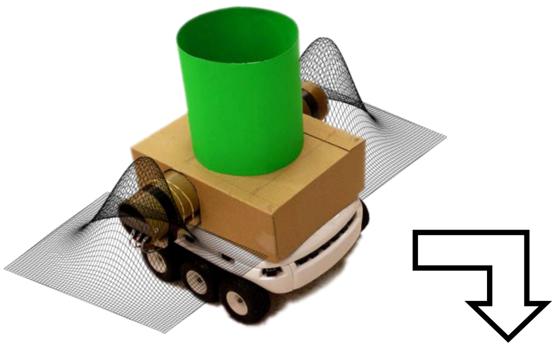
Quasi-Continuous Input

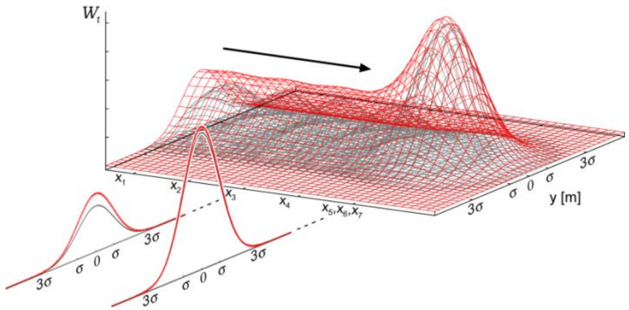


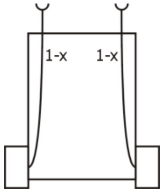


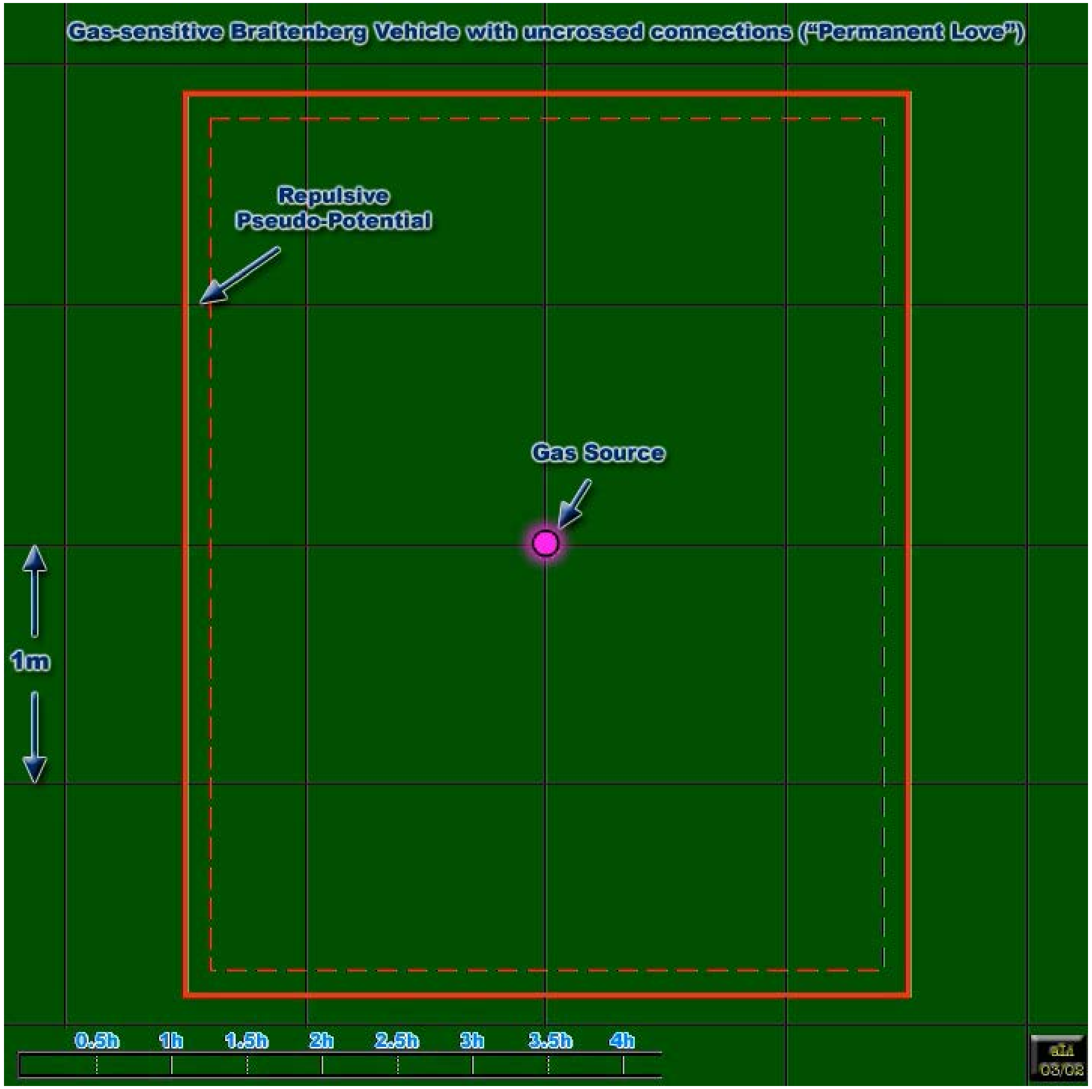
GDM with Quasi-Continuous Input

[Lilienthal et al., AR 2004]





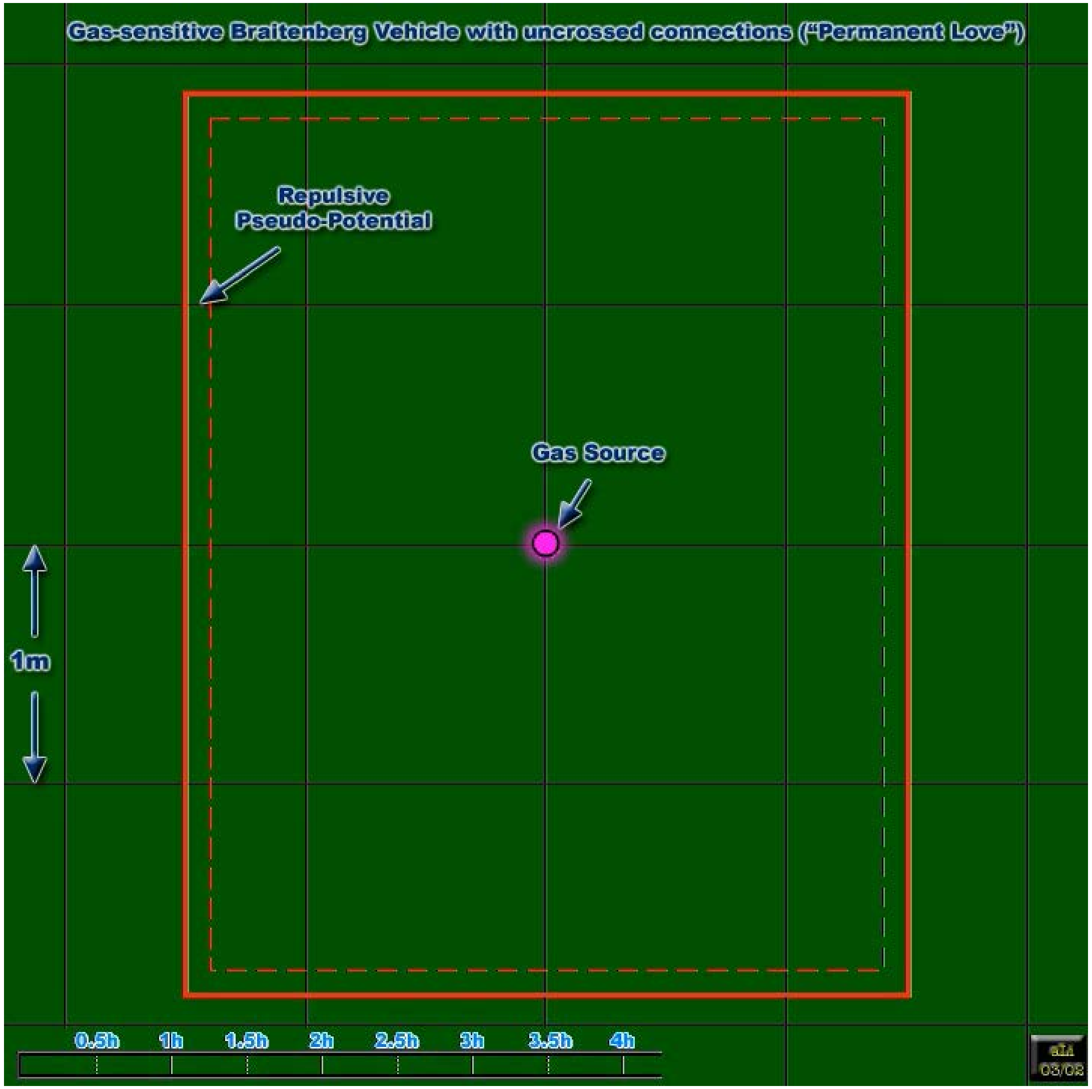




GDM with Quasi-Continuous Input

- Simplifying Assumptions
  - 2D problem
  - Underlying distribution is constant over time
  - One known gas present
  - Ideal sensor
  - No calibration issues
  - Simple, radial correlation of sensor measurements

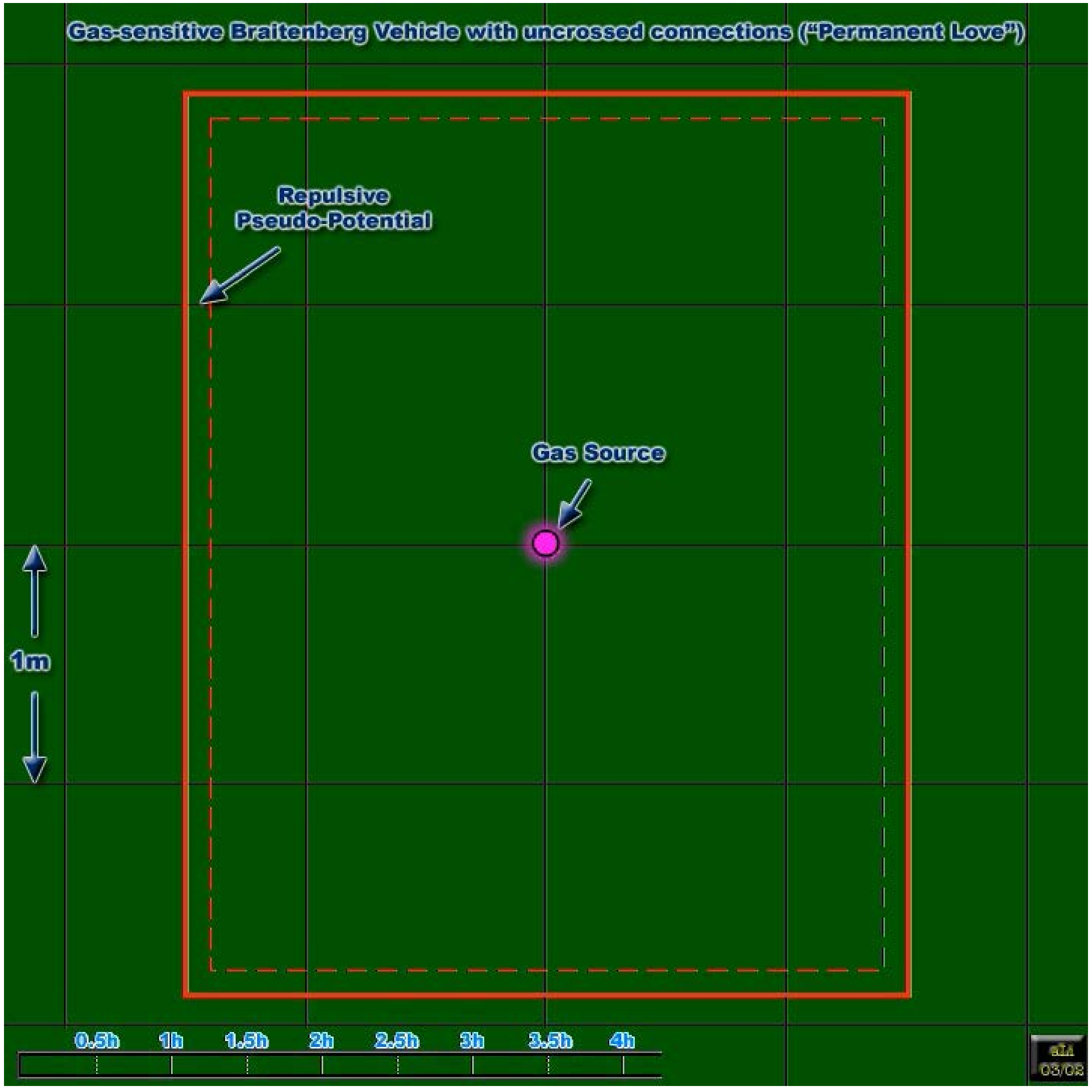
[Lilienthal et al., AR 2004]



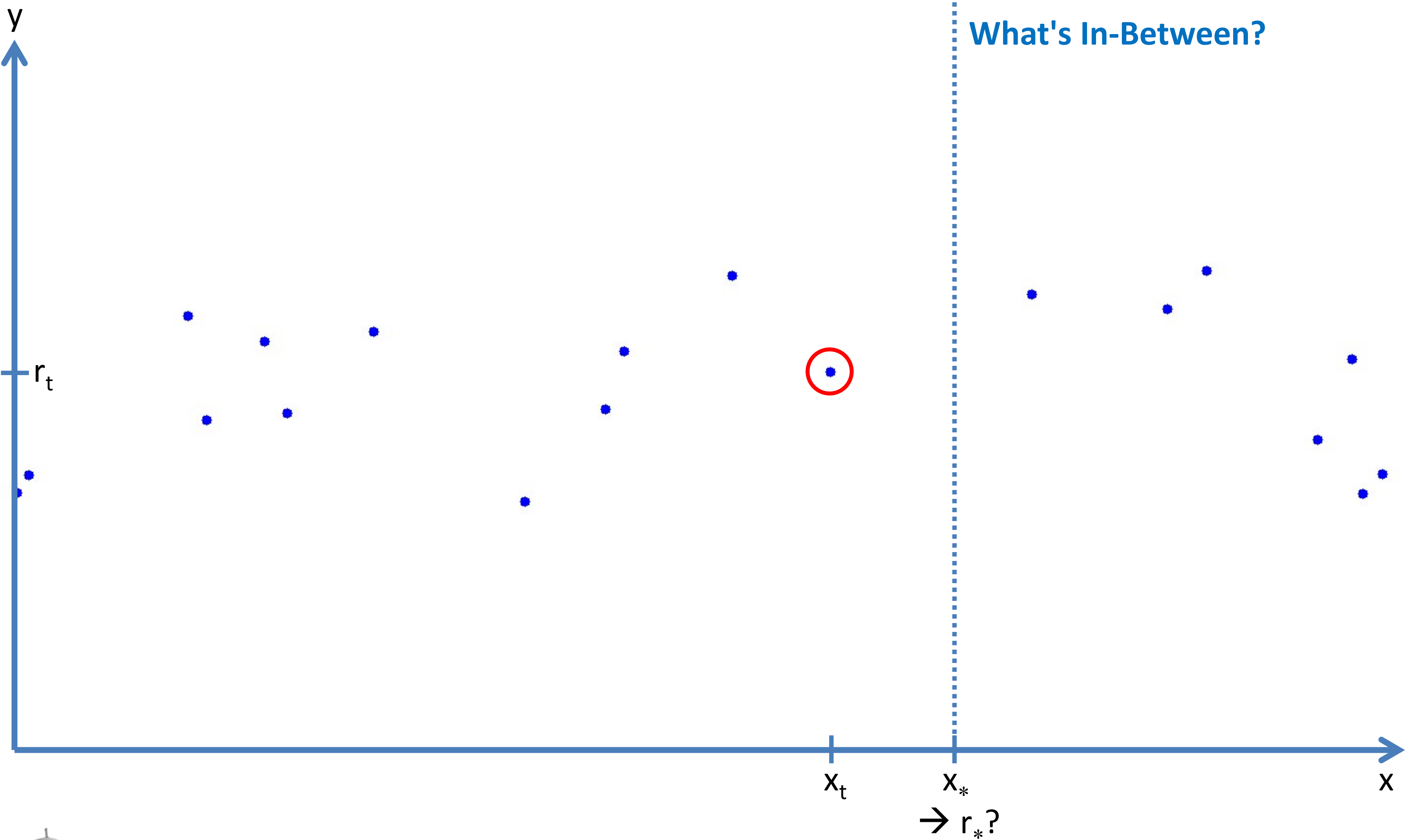
GDM with Quasi-Continuous Input

[Lilienthal et al., AR 2004]

- Simplifying Assumptions
  - 2D → 1D problem
  - Underlying distribution is constant over time
  - One known gas present
  - Ideal sensor
  - No calibration issues
  - Simple, radial correlation → distance-based of sensor measurements

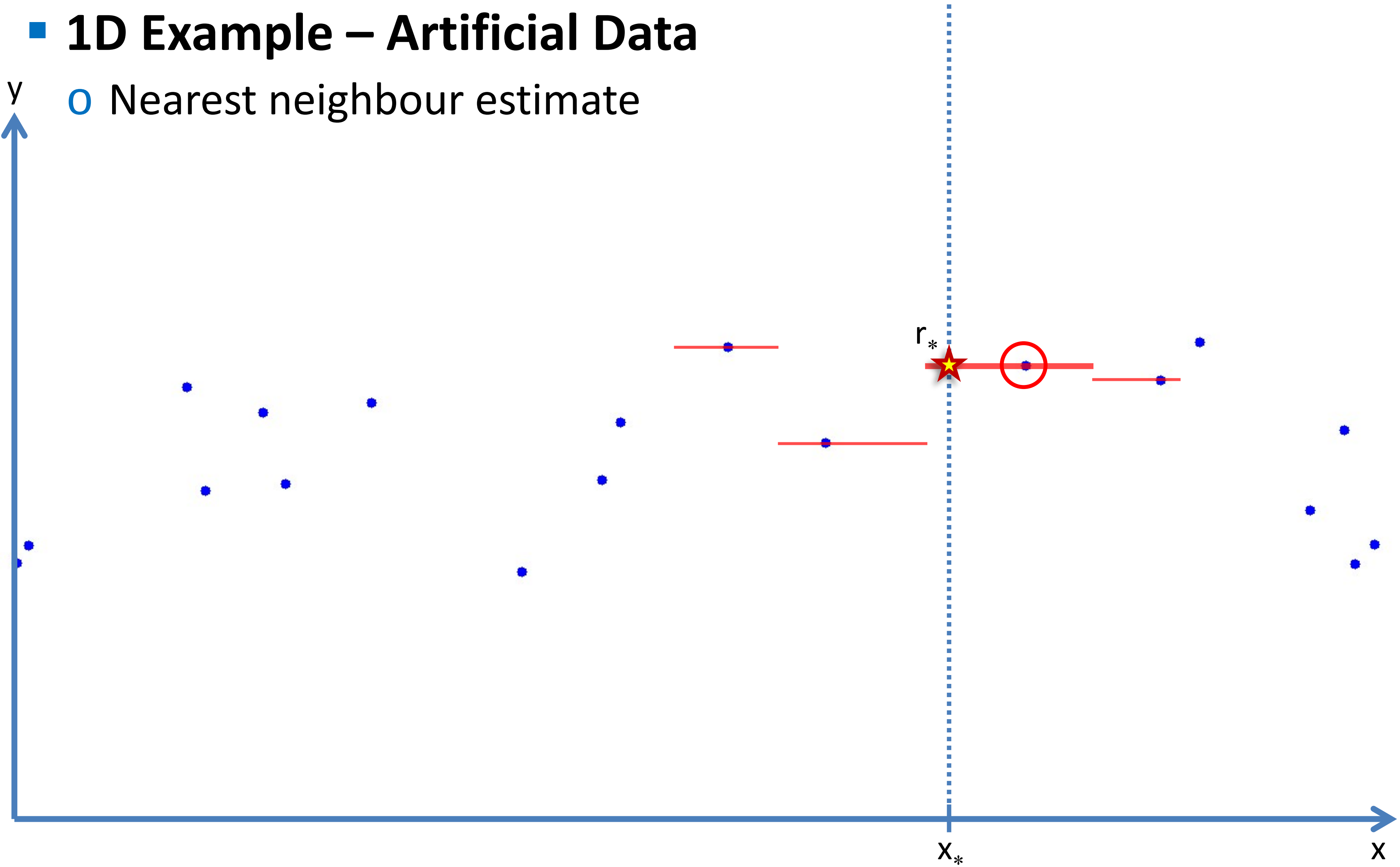


1D Example – Artificial Data (18 data points)

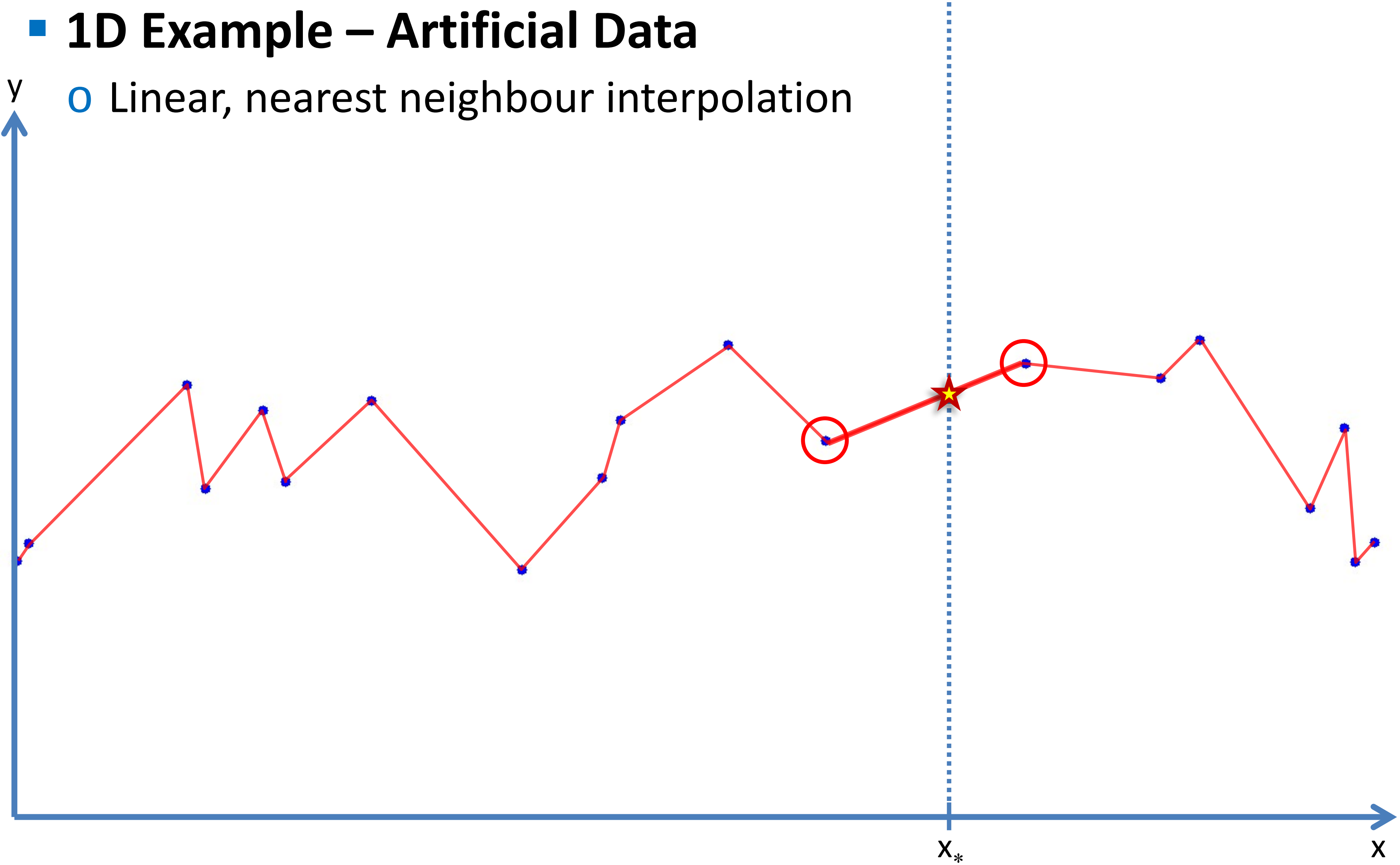


1D Example – Artificial Data

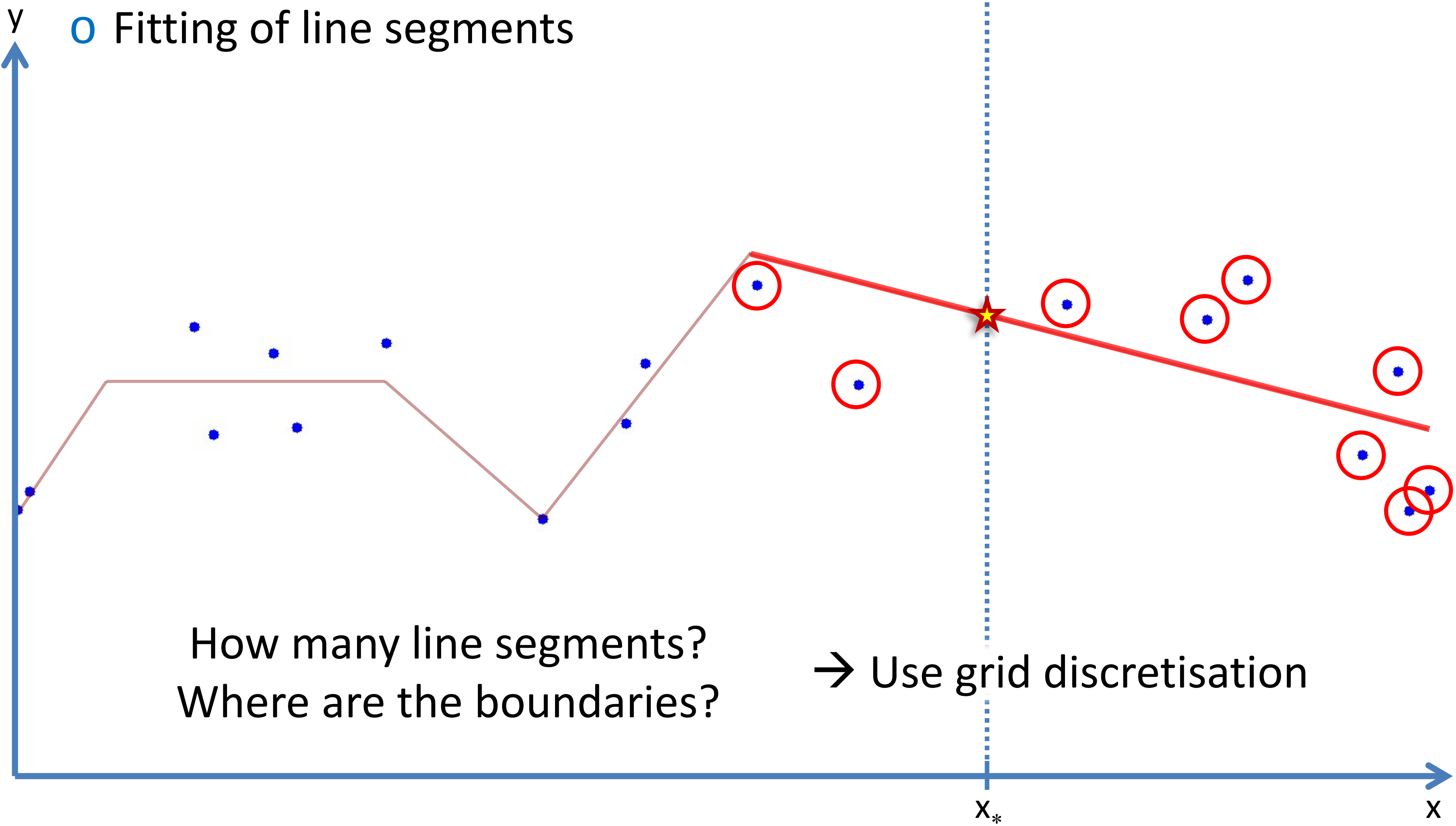
- Nearest neighbour estimate



- **1D Example – Artificial Data**
  - Linear, nearest neighbour interpolation



- **1D Example – Artificial Data**
  - Fitting of line segments

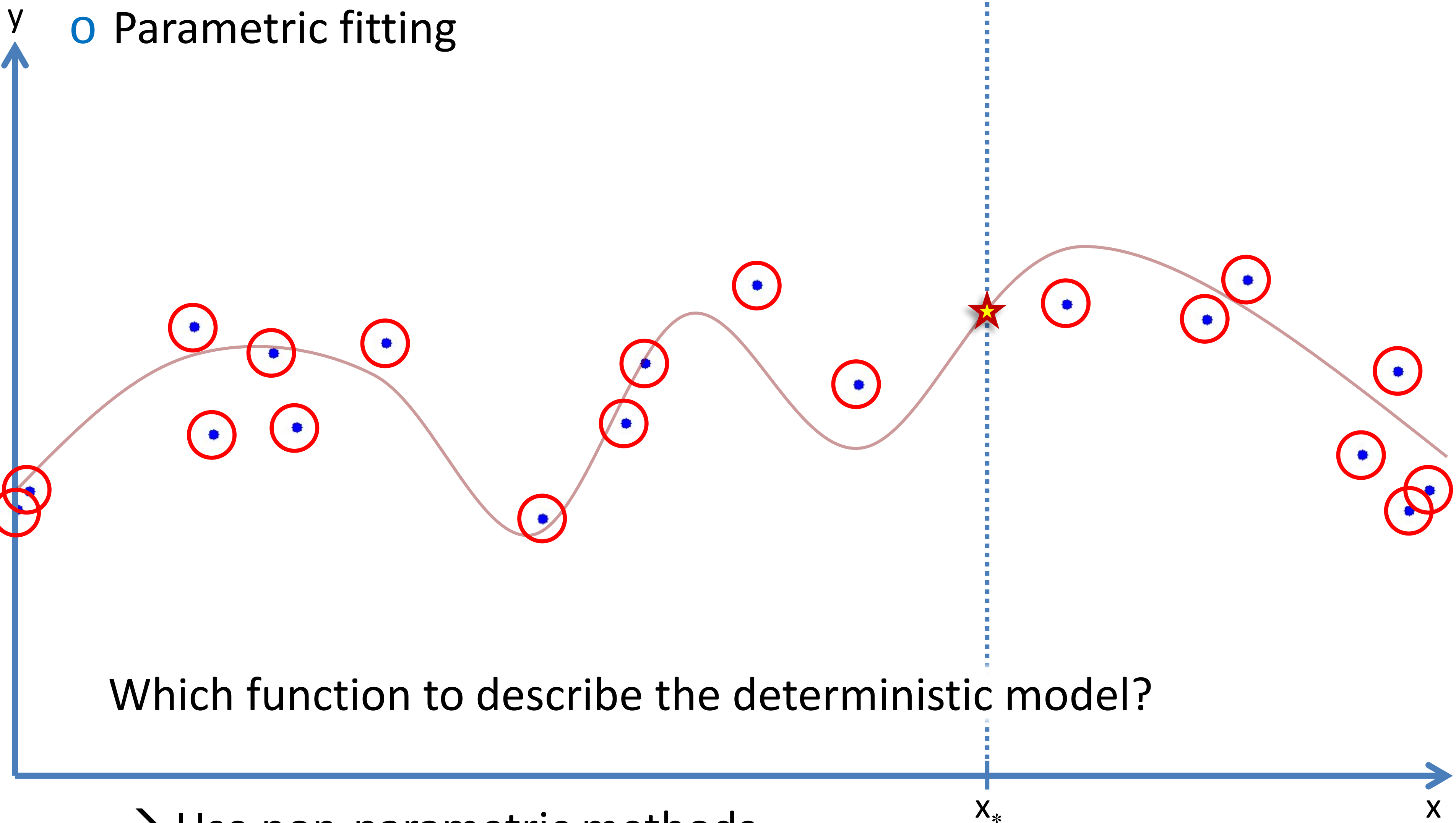


How many line segments?
Where are the boundaries?

→ Use grid discretisation

1D Example – Artificial Data

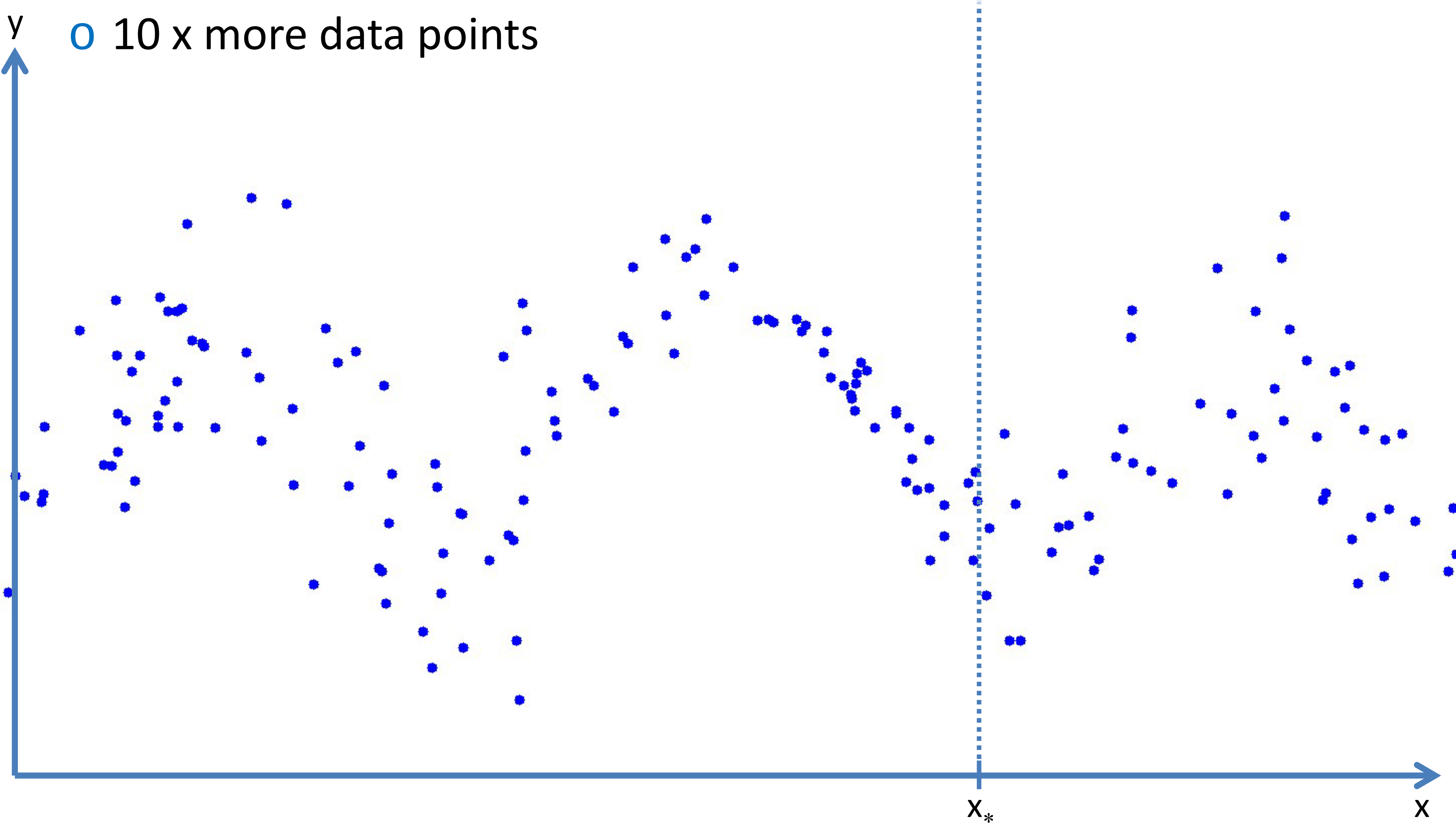
- Parametric fitting



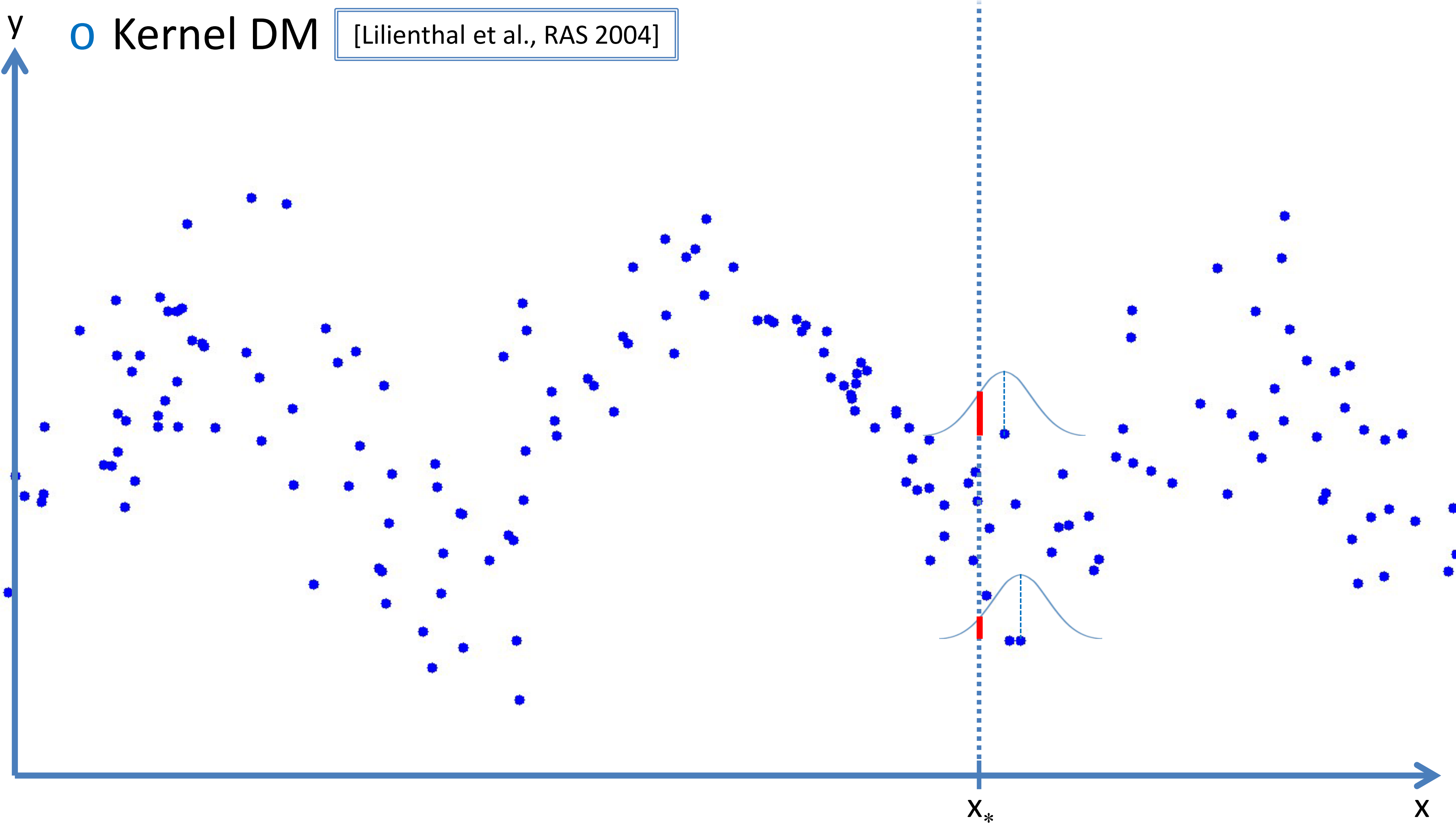
Which function to describe the deterministic model?

→ Use non-parametric methods

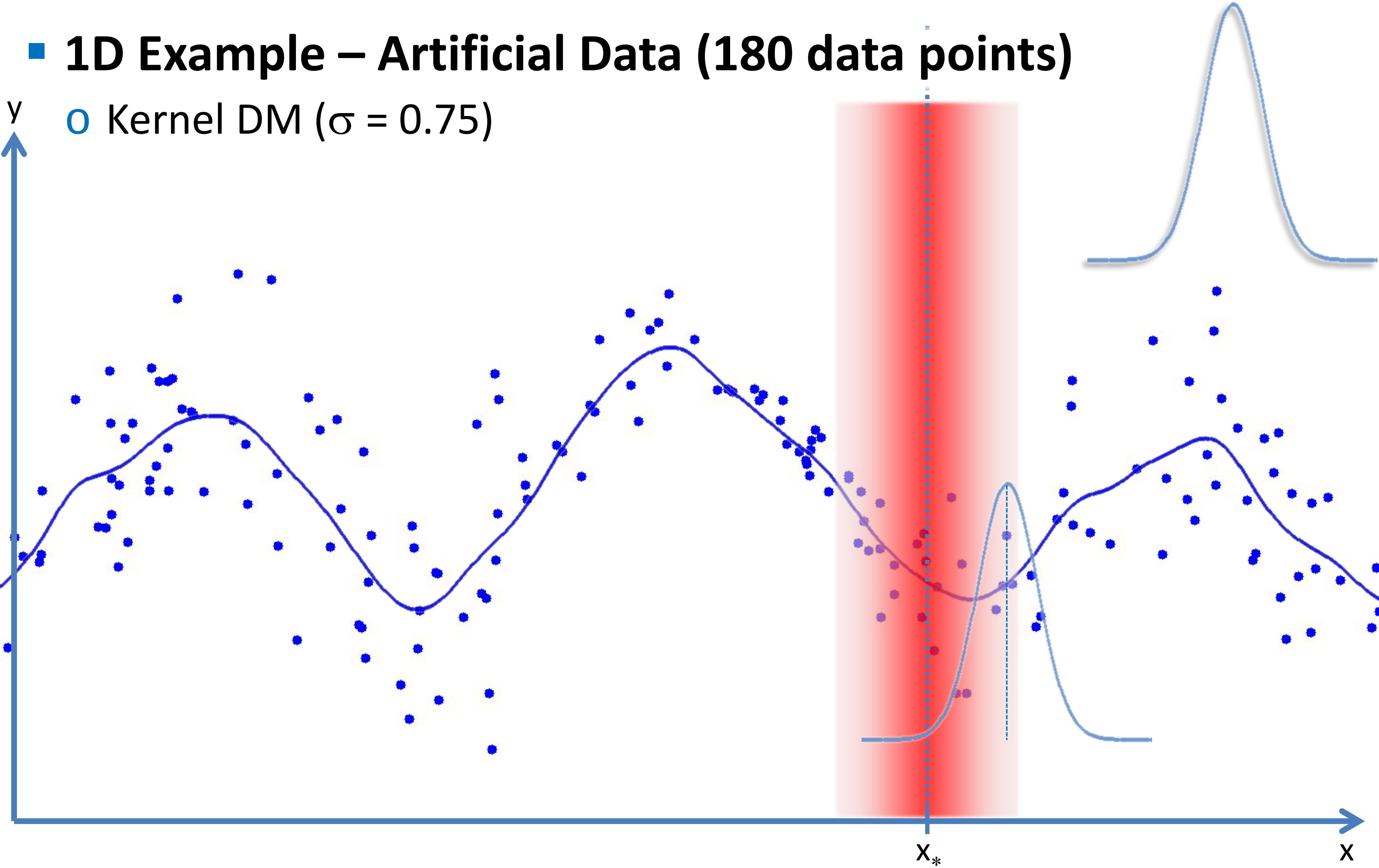
- **1D Example – Artificial Data (Less Sparse/180 data points)**
  - 10 x more data points



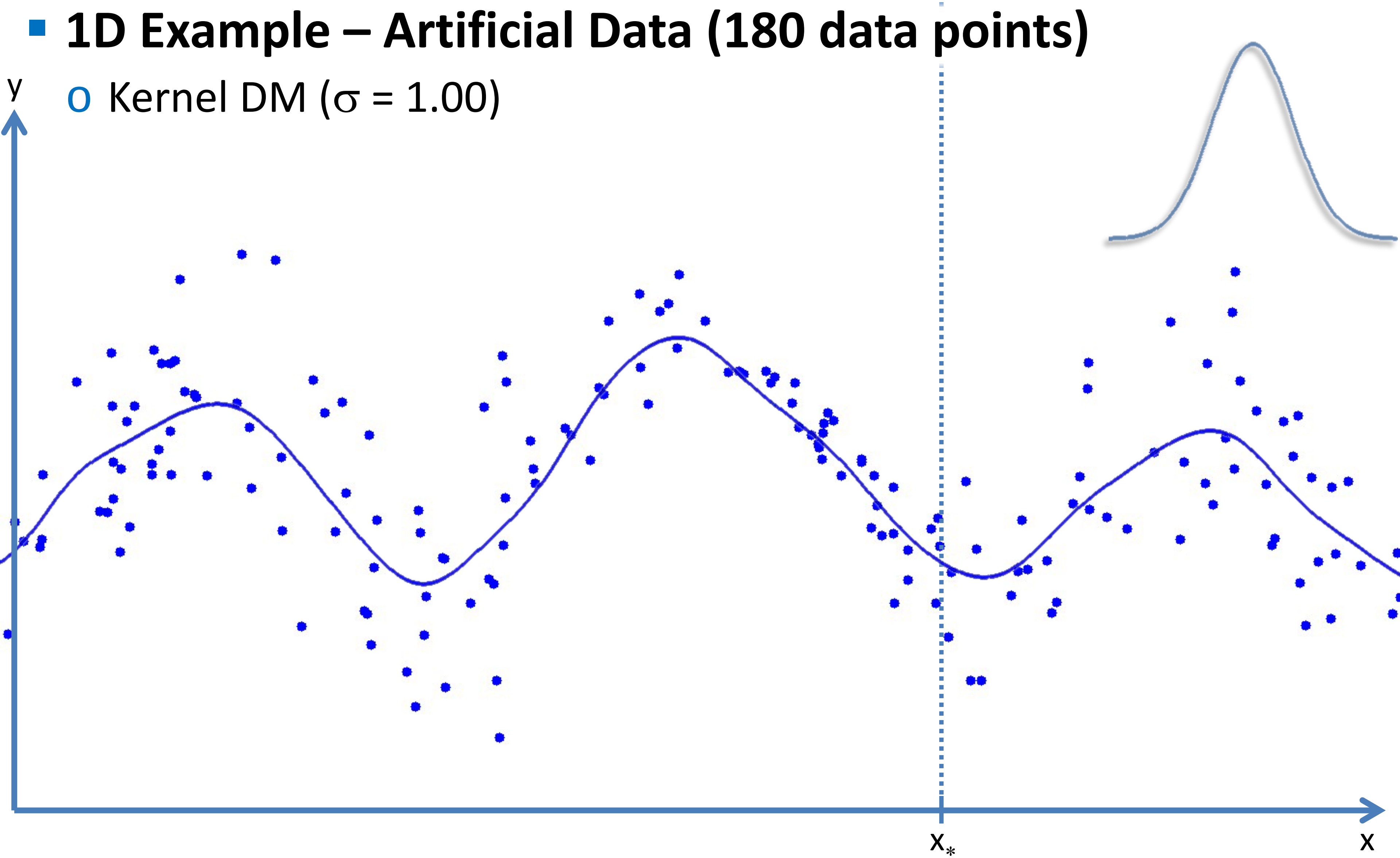
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM [Lilienthal et al., RAS 2004]



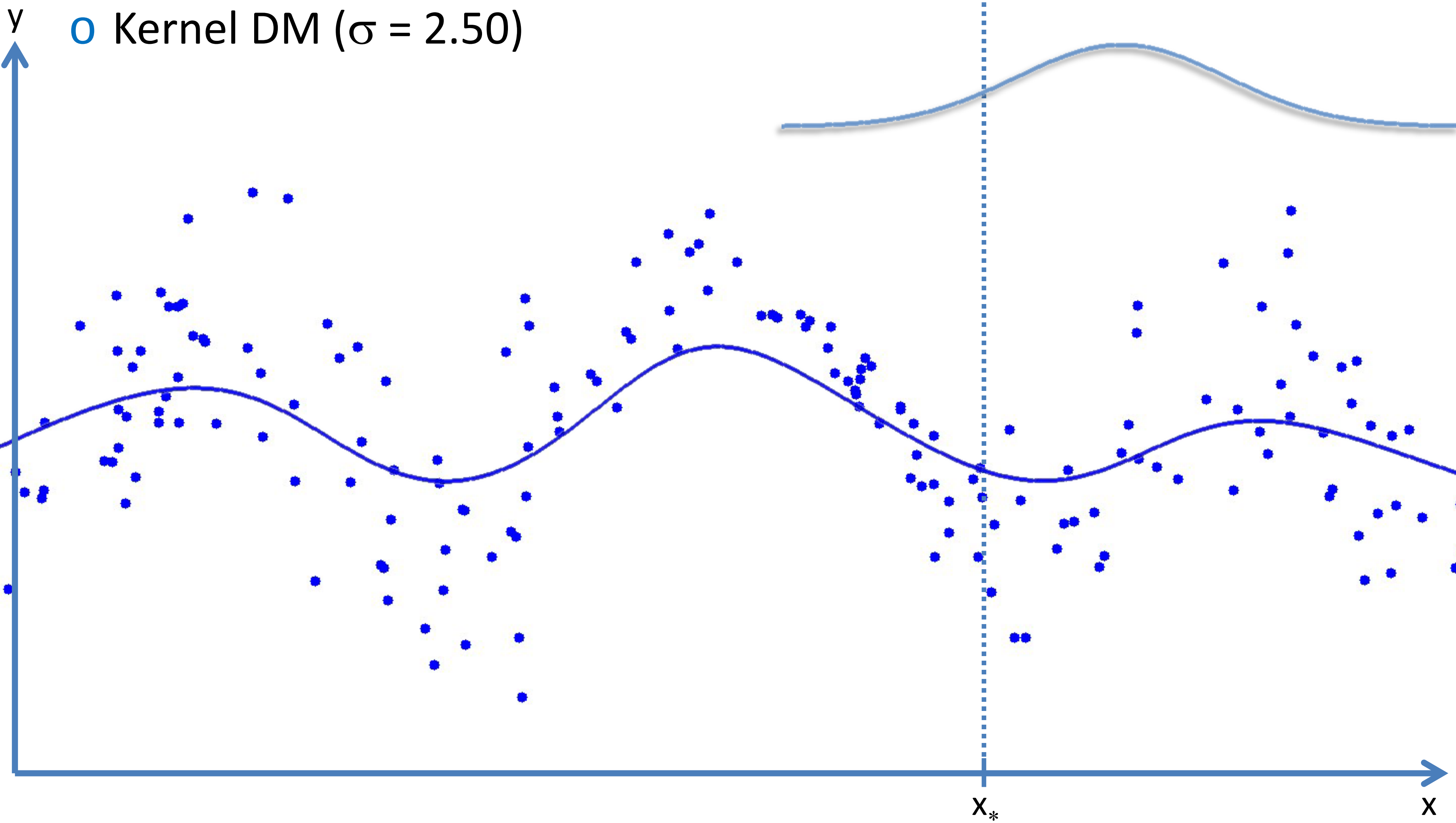
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM (σ = 0.75)



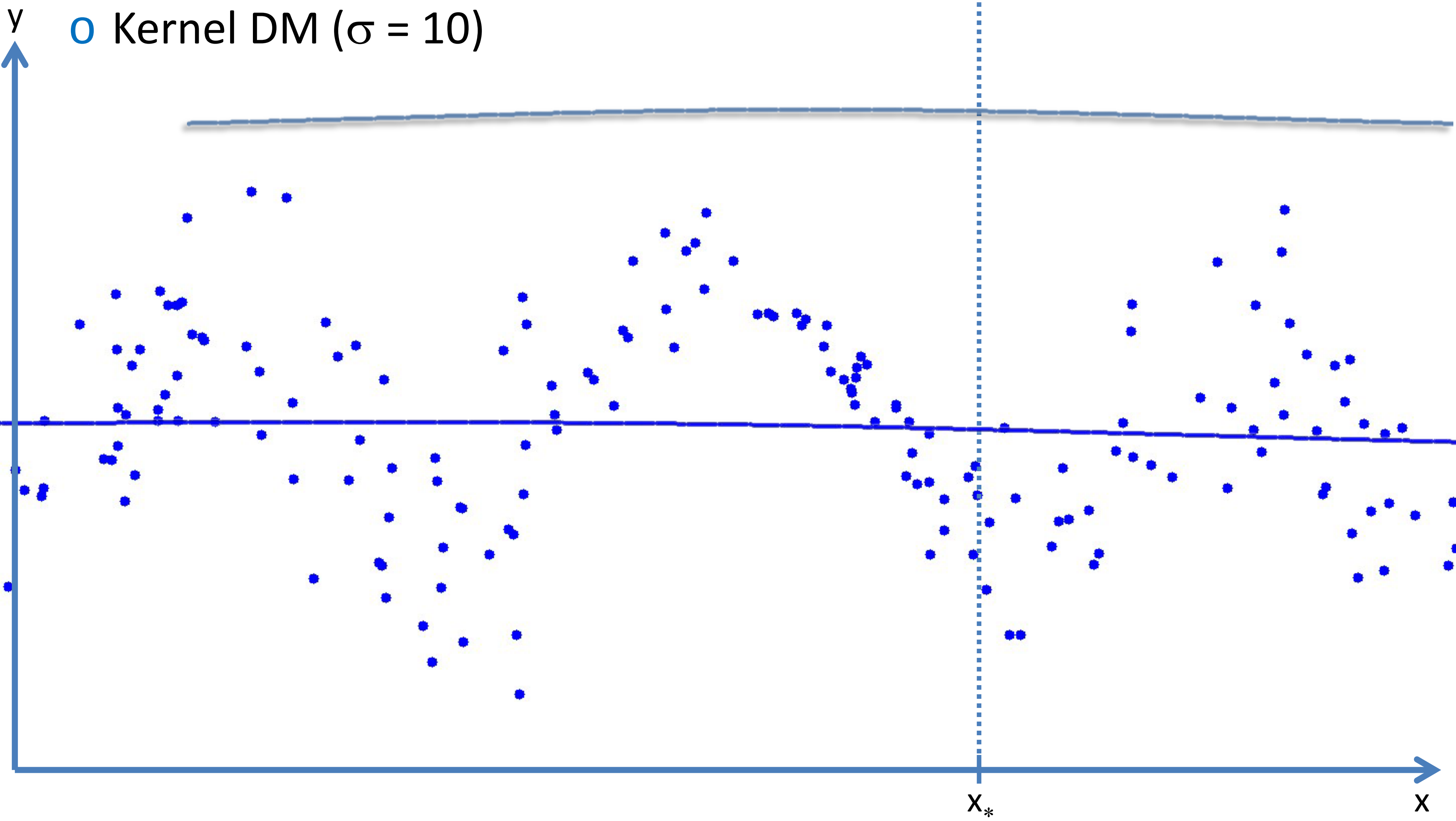
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM (σ = 1.00)



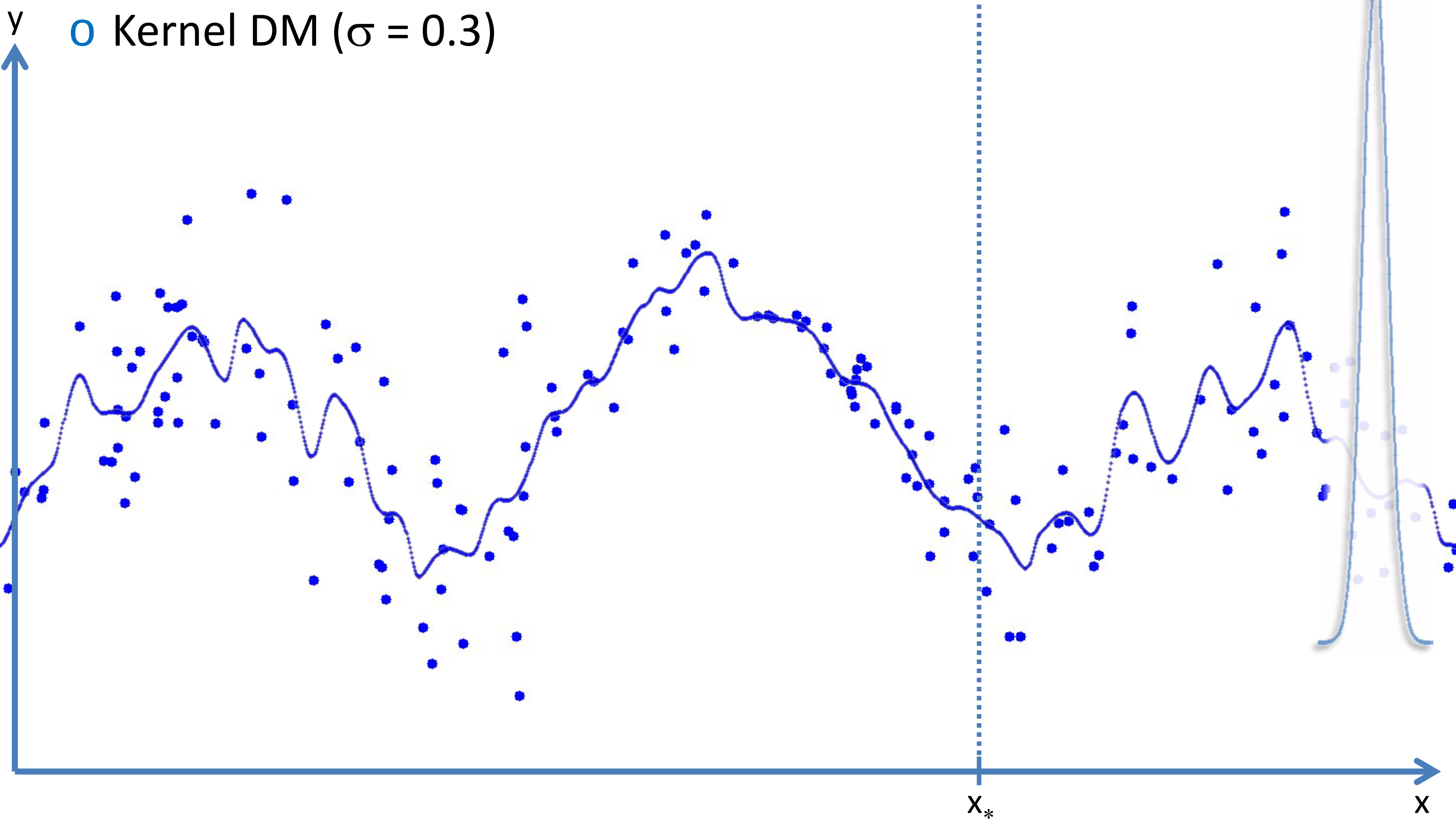
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM (σ = 2.50)



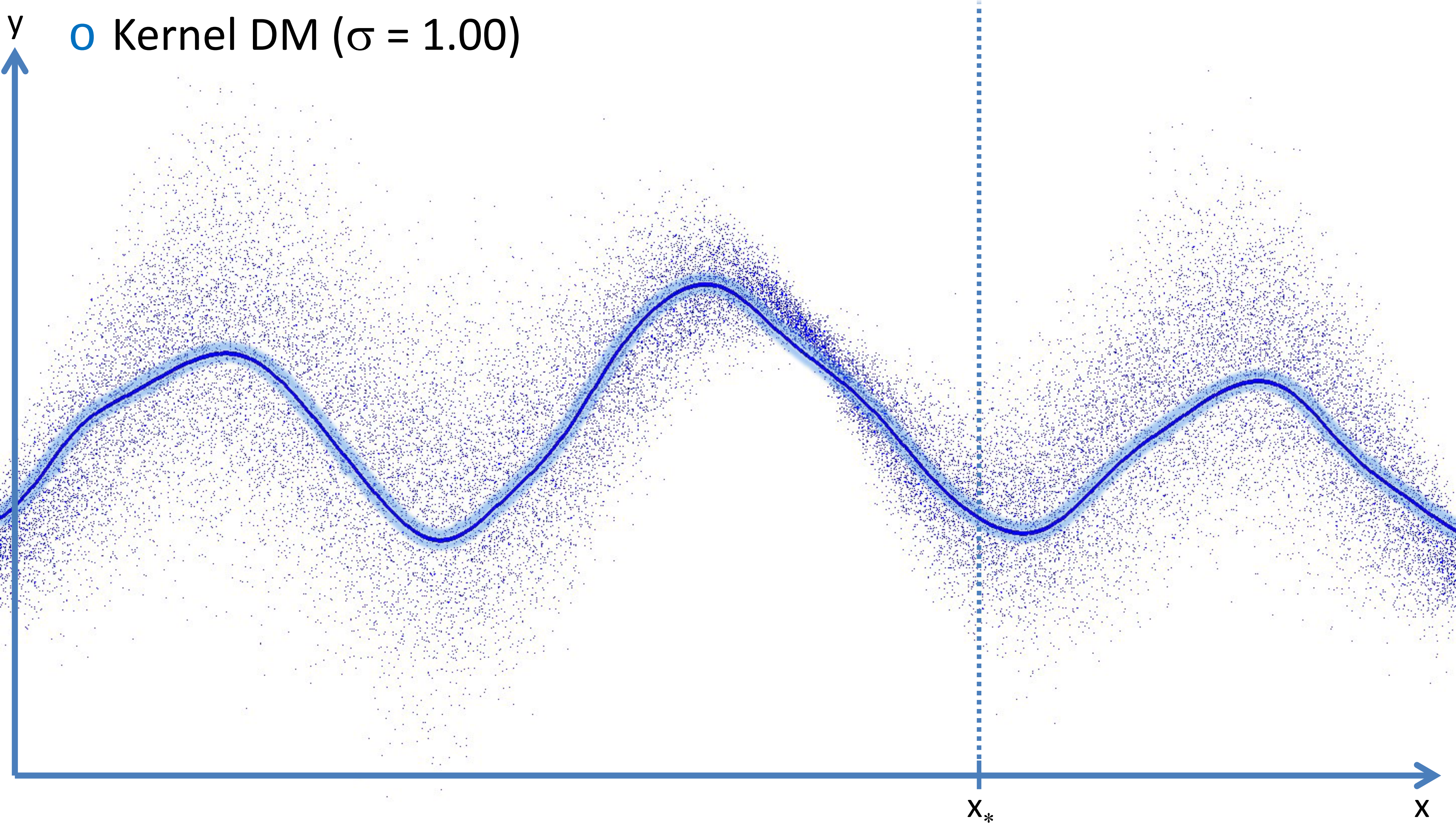
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM (σ = 10)



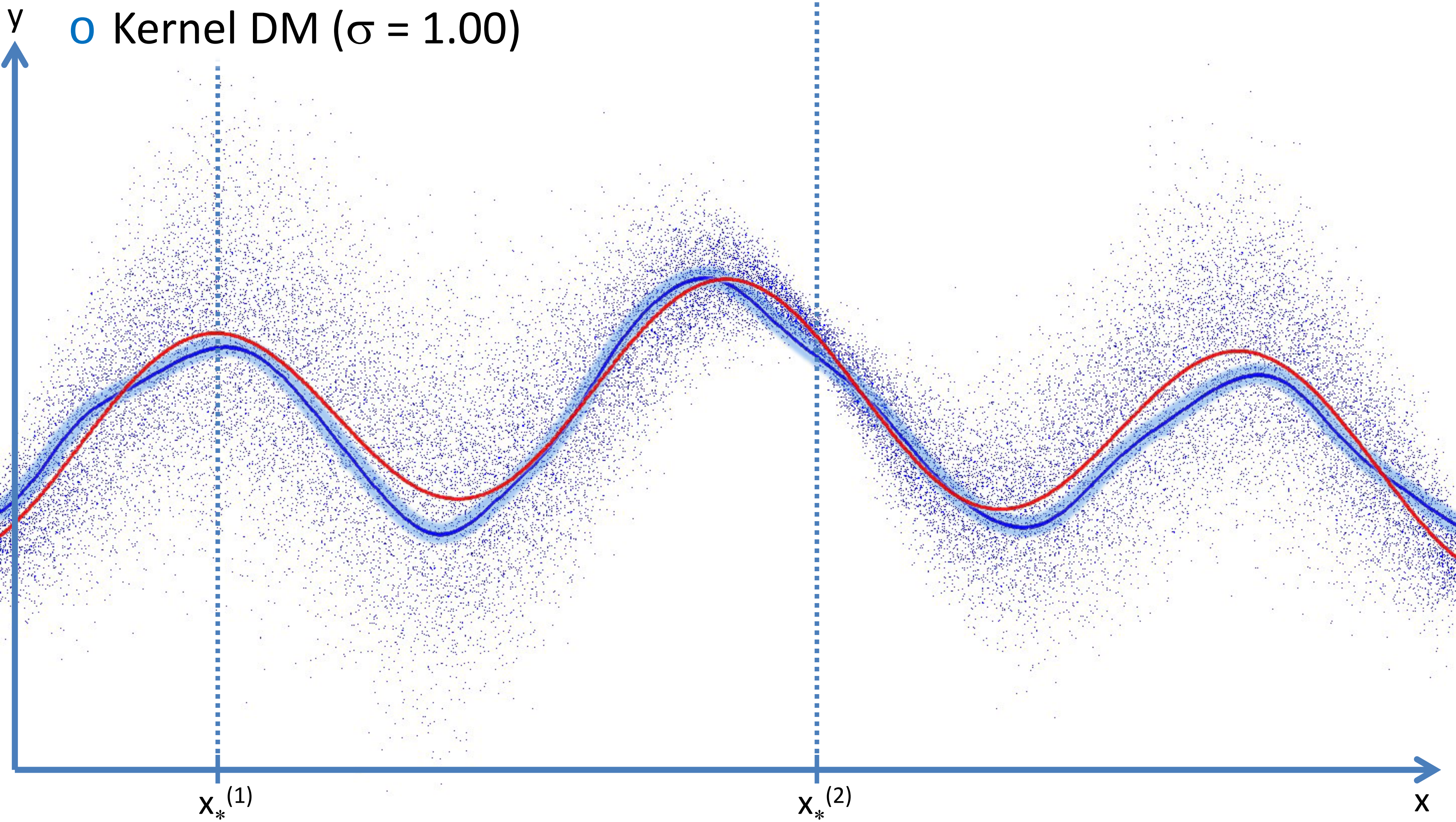
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM (σ = 0.3)



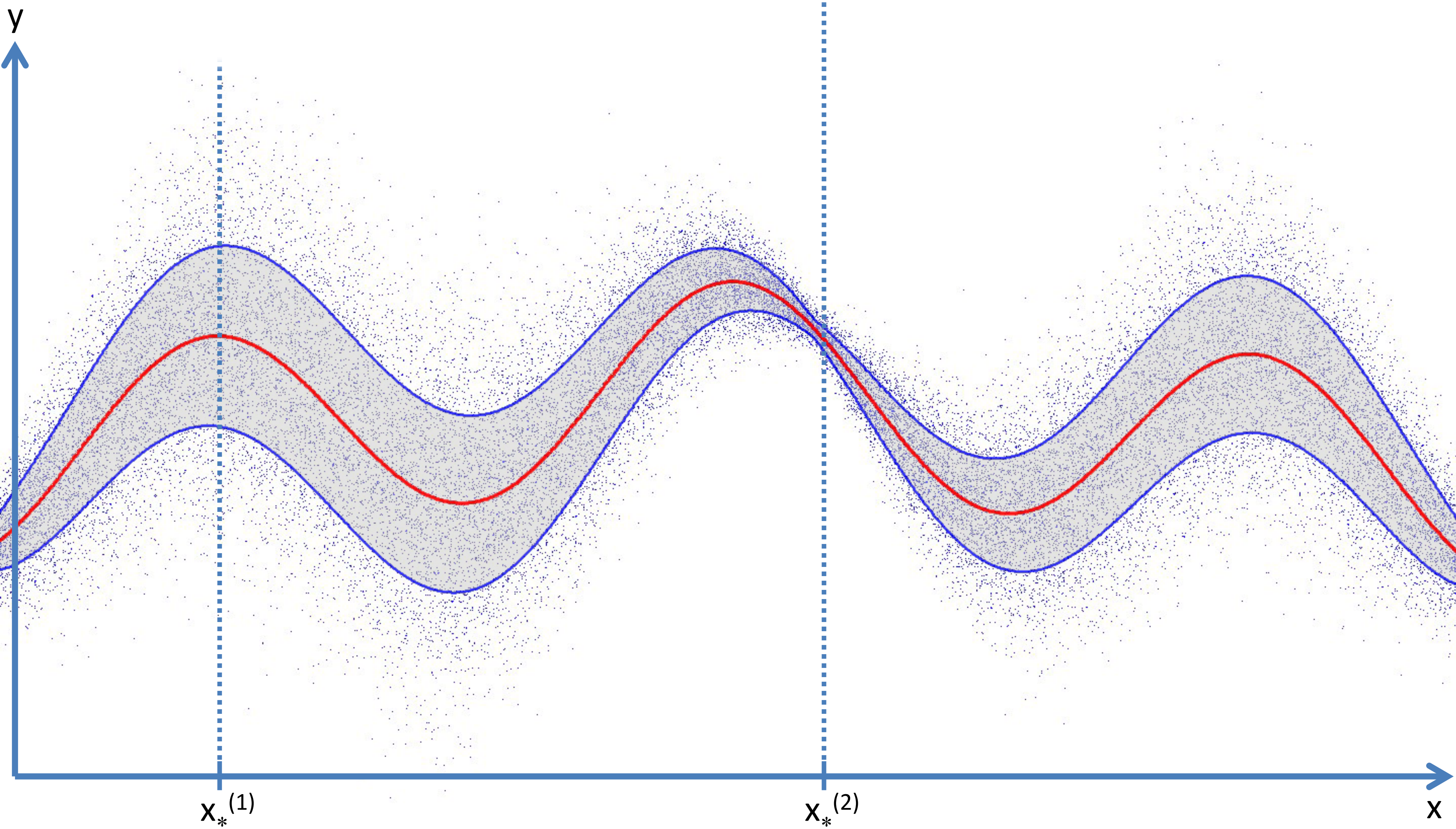
- **1D Example – Artificial Data (36000 data points)**
  - Kernel DM (σ = 1.00)



- **1D Example – Artificial Data (36000 data points)**
  - Kernel DM (σ = 1.00)

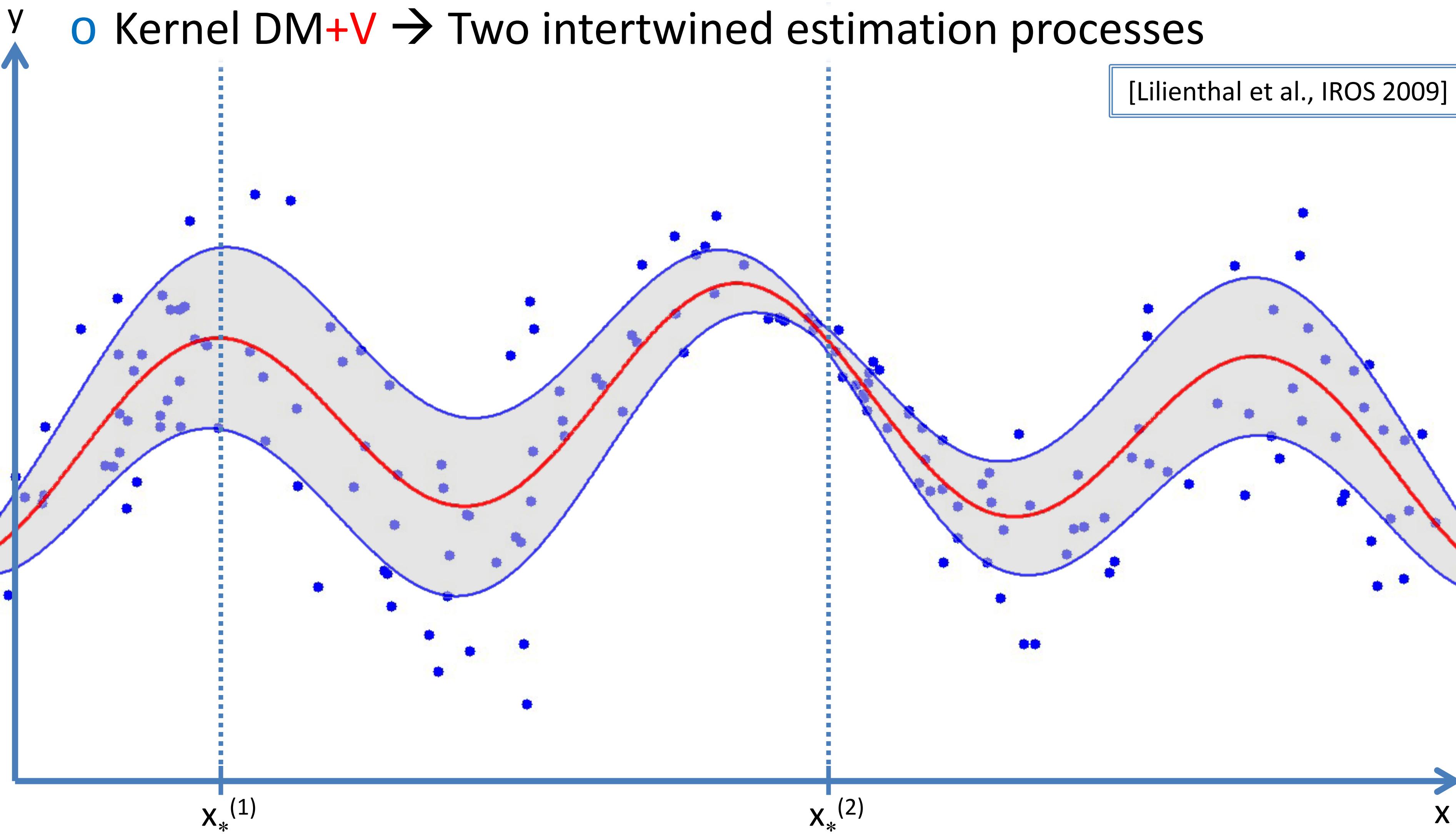


- **1D Example – Artificial Data (36000 data points)**

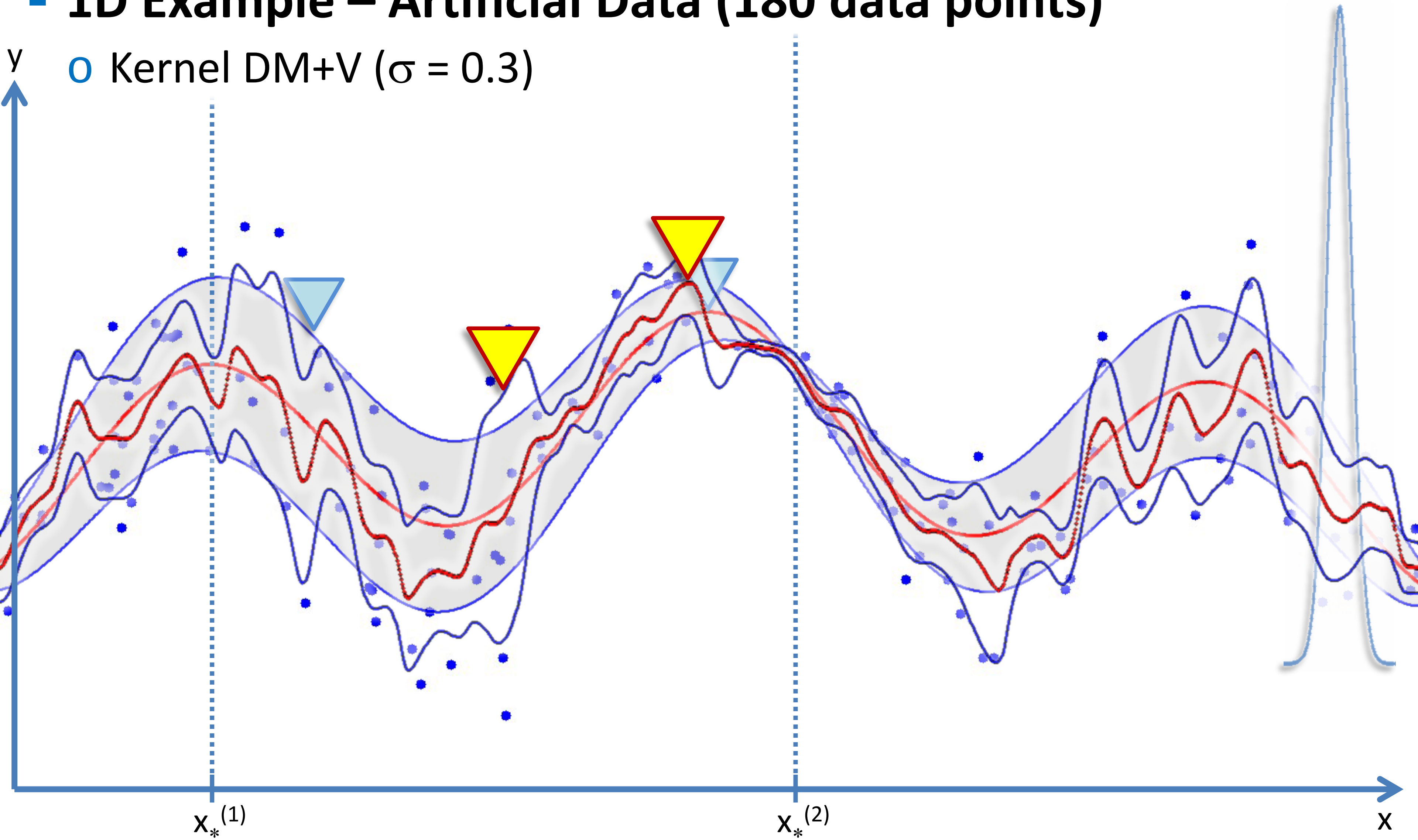


- **1D Example – Artificial Data (180 data points)**
  - o Kernel DM+V → Two intertwined estimation processes

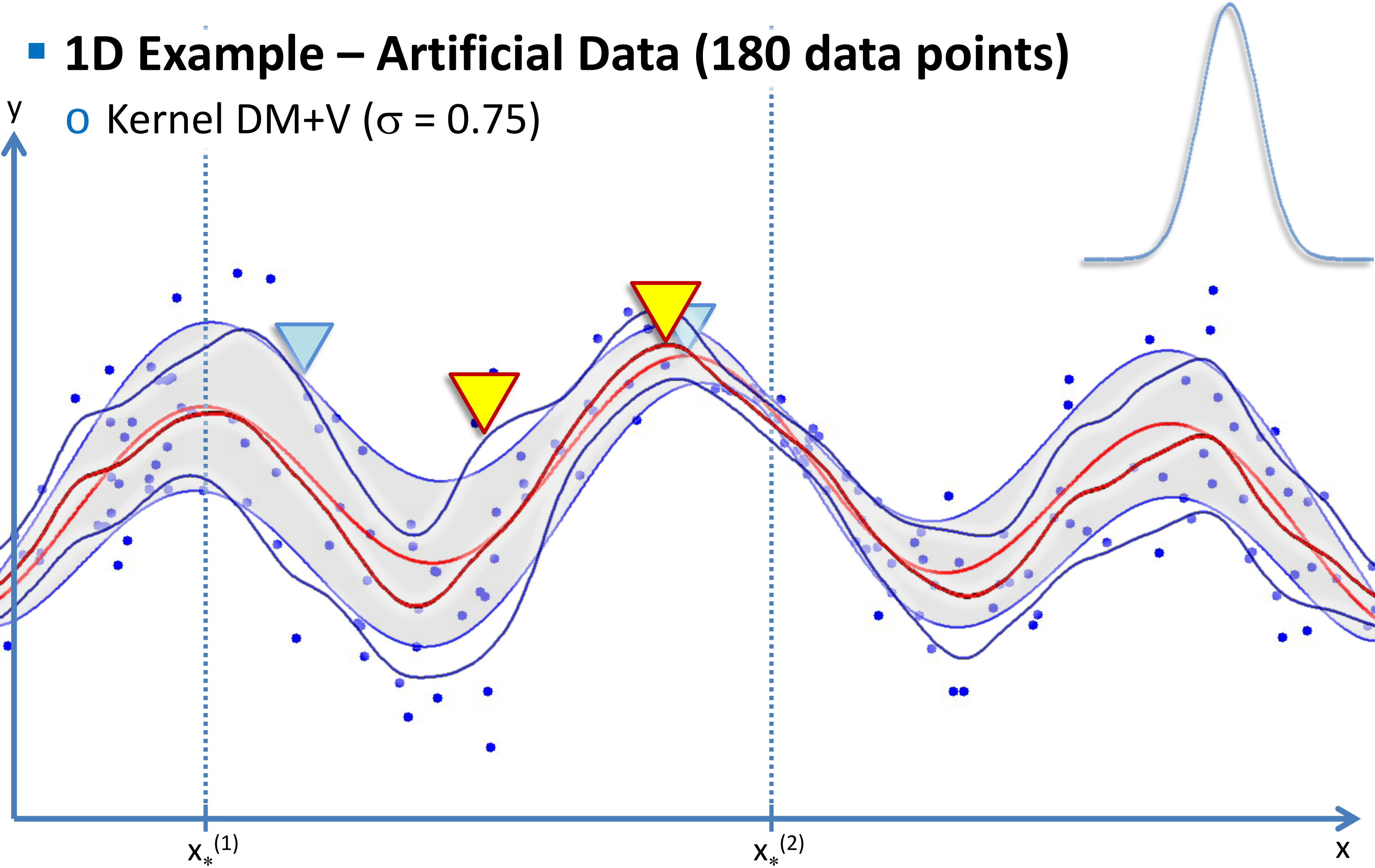
[Lilienthal et al., IROS 2009]



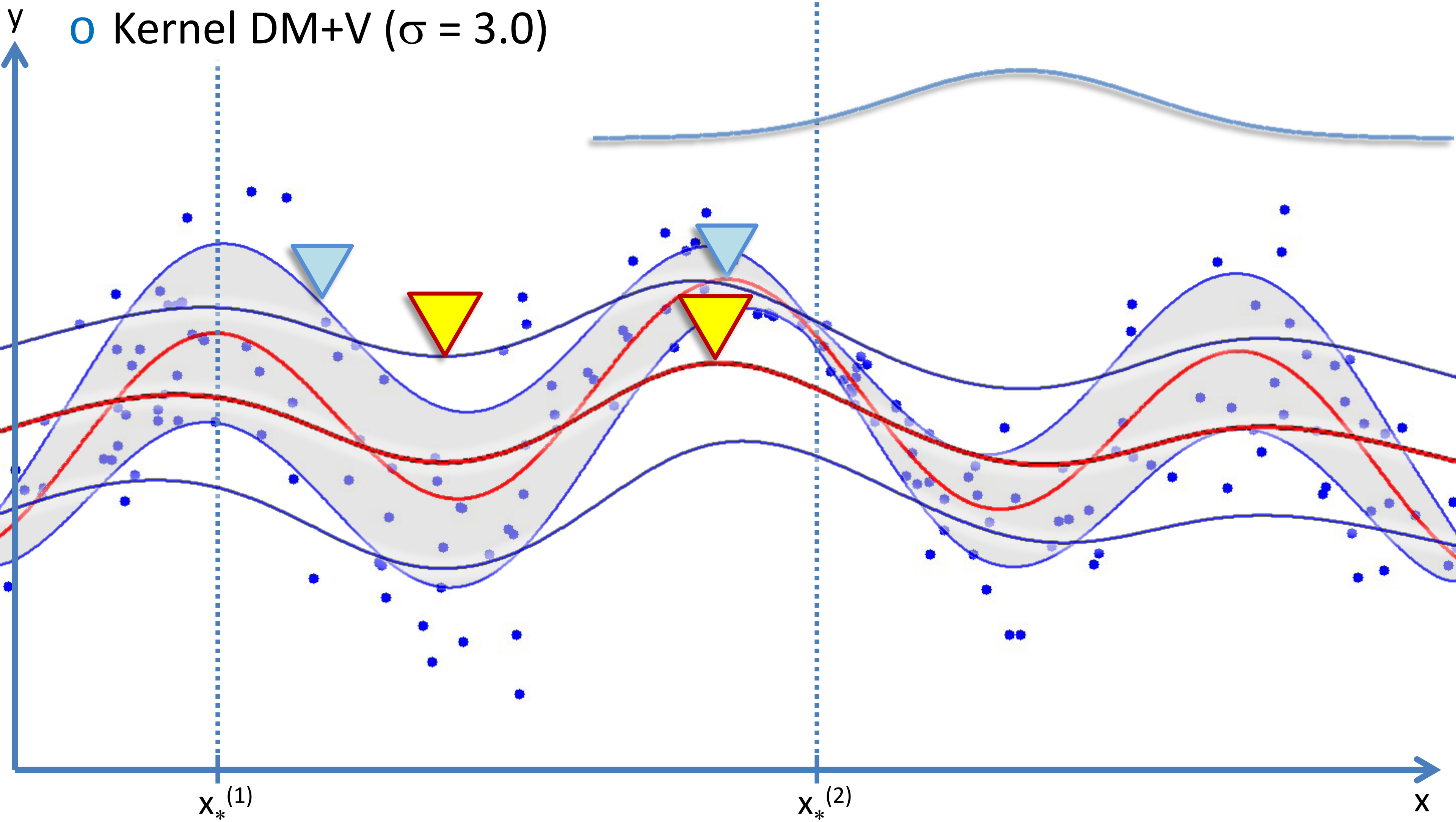
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM+V ($\sigma = 0.3$)



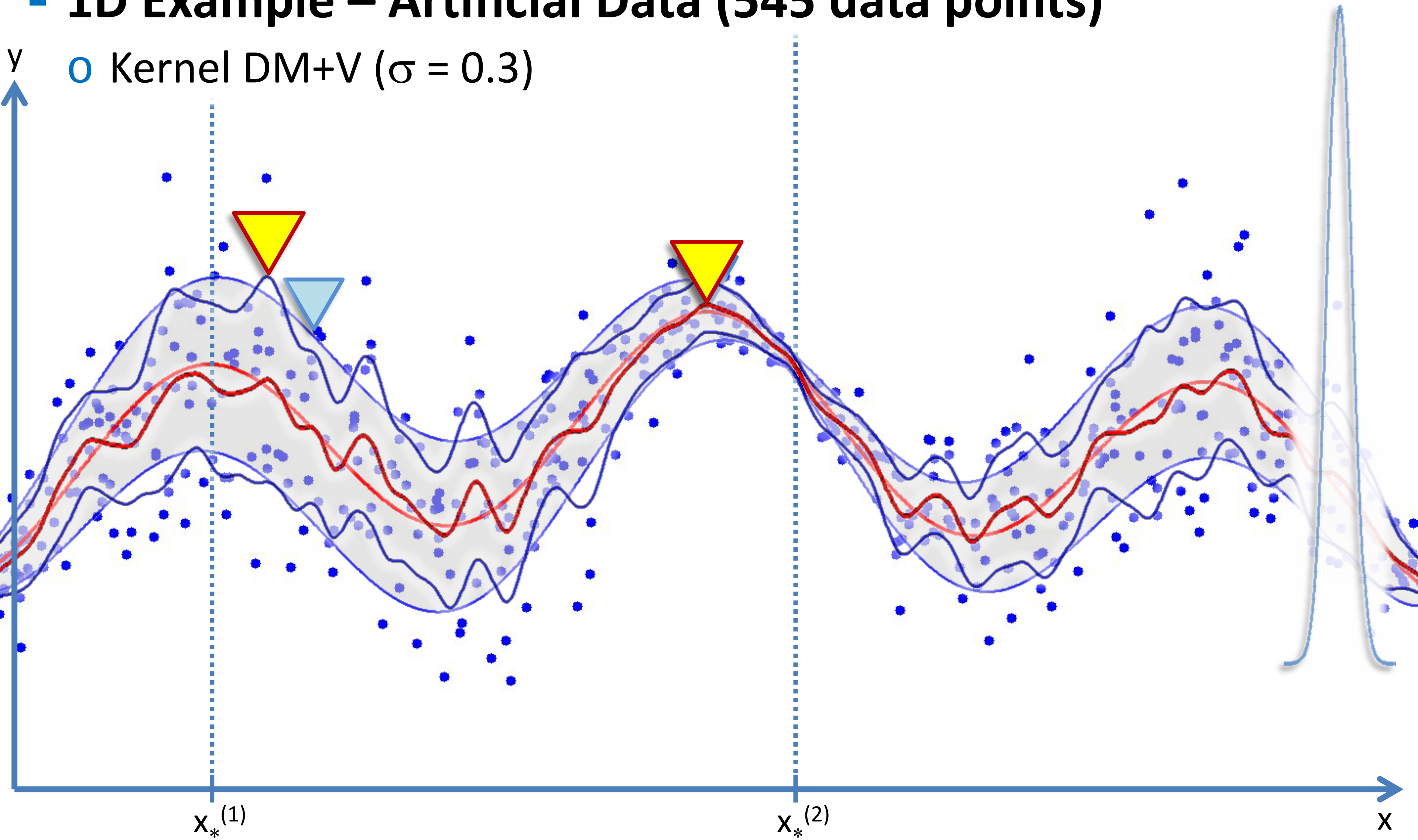
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM+V ($\sigma = 0.75$)



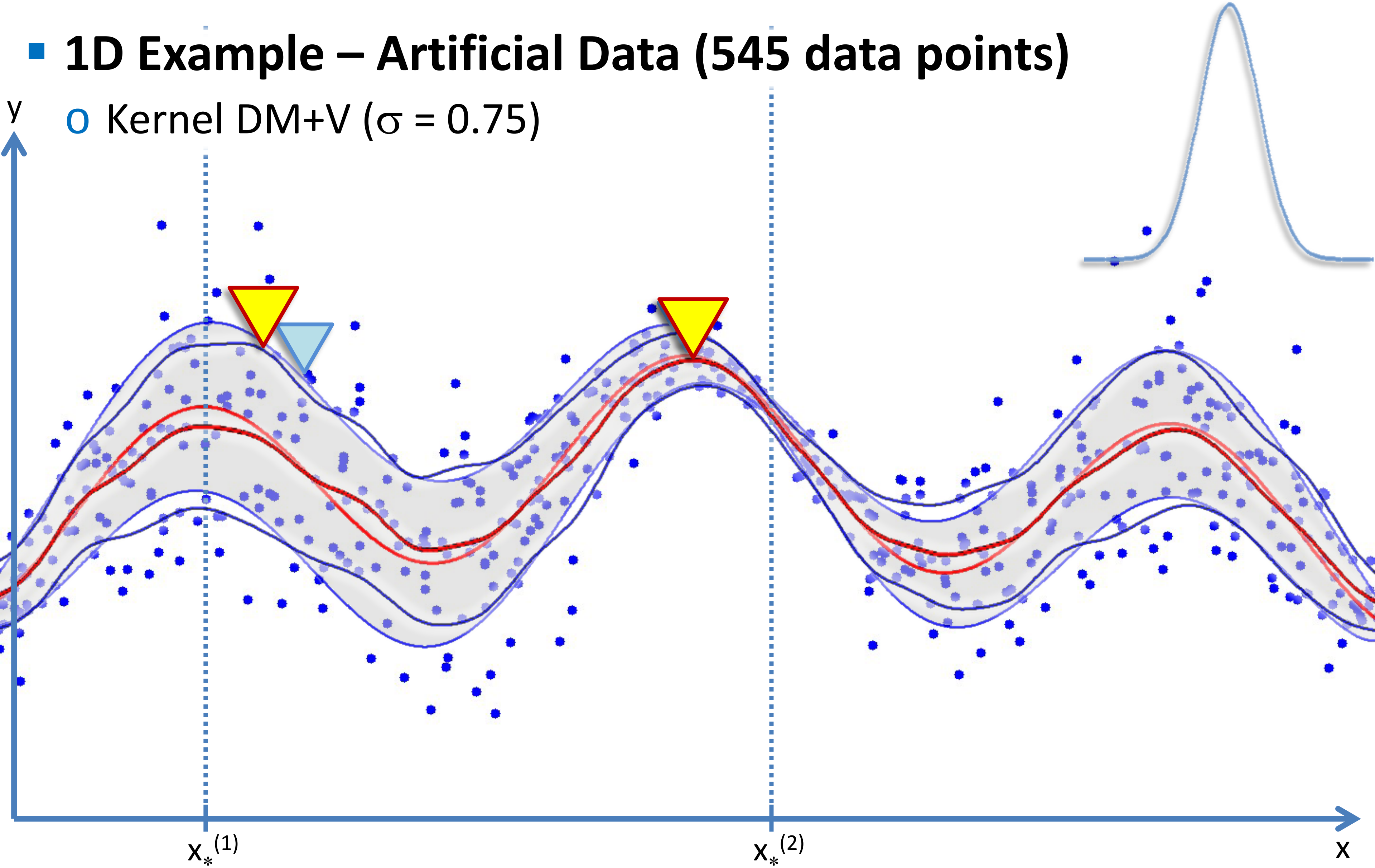
- **1D Example – Artificial Data (180 data points)**
  - Kernel DM+V (σ = 3.0)



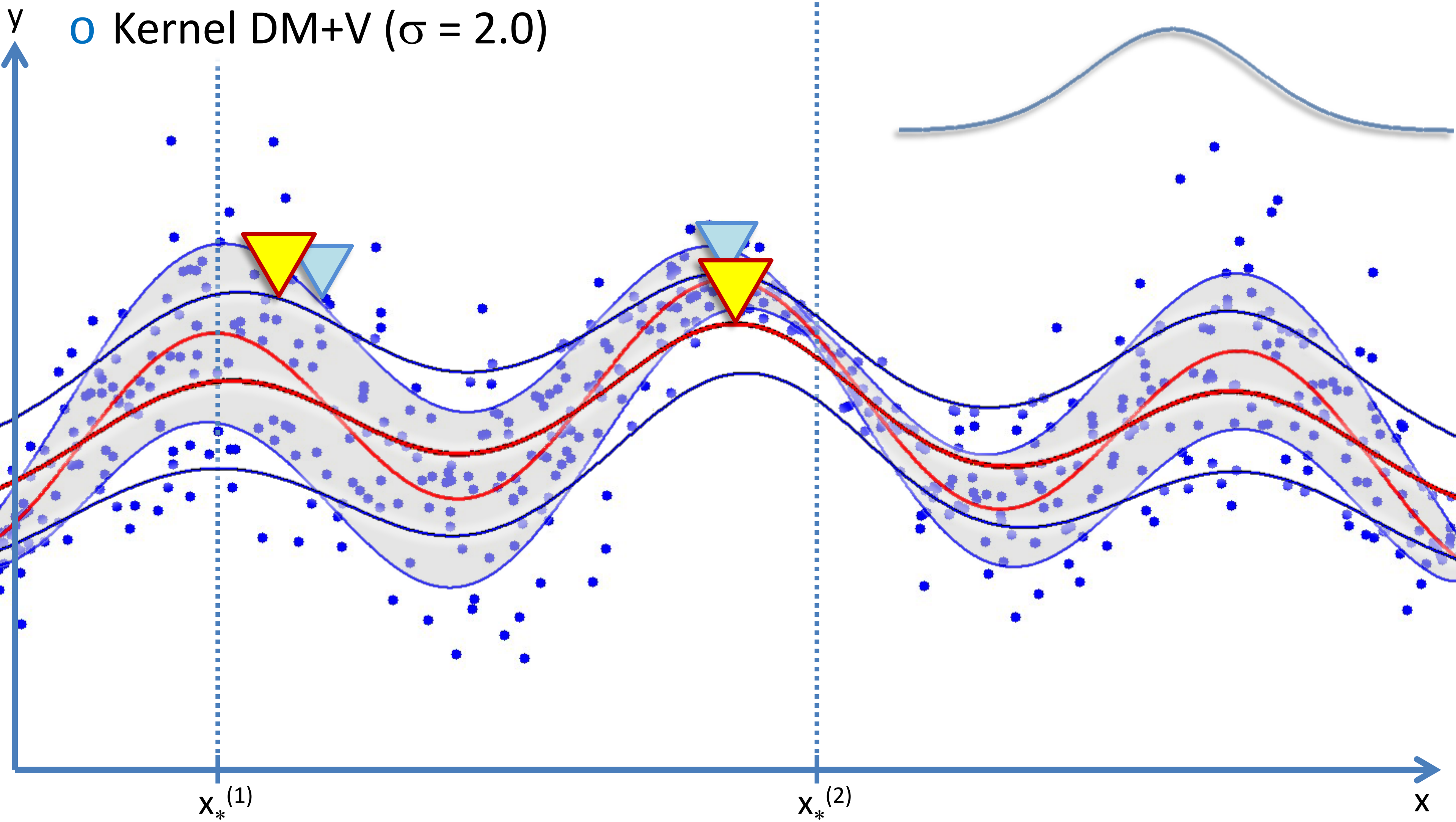
- **1D Example – Artificial Data (545 data points)**
  - o Kernel DM+V (σ = 0.3)



- **1D Example – Artificial Data (545 data points)**
  - Kernel DM+V (σ = 0.75)

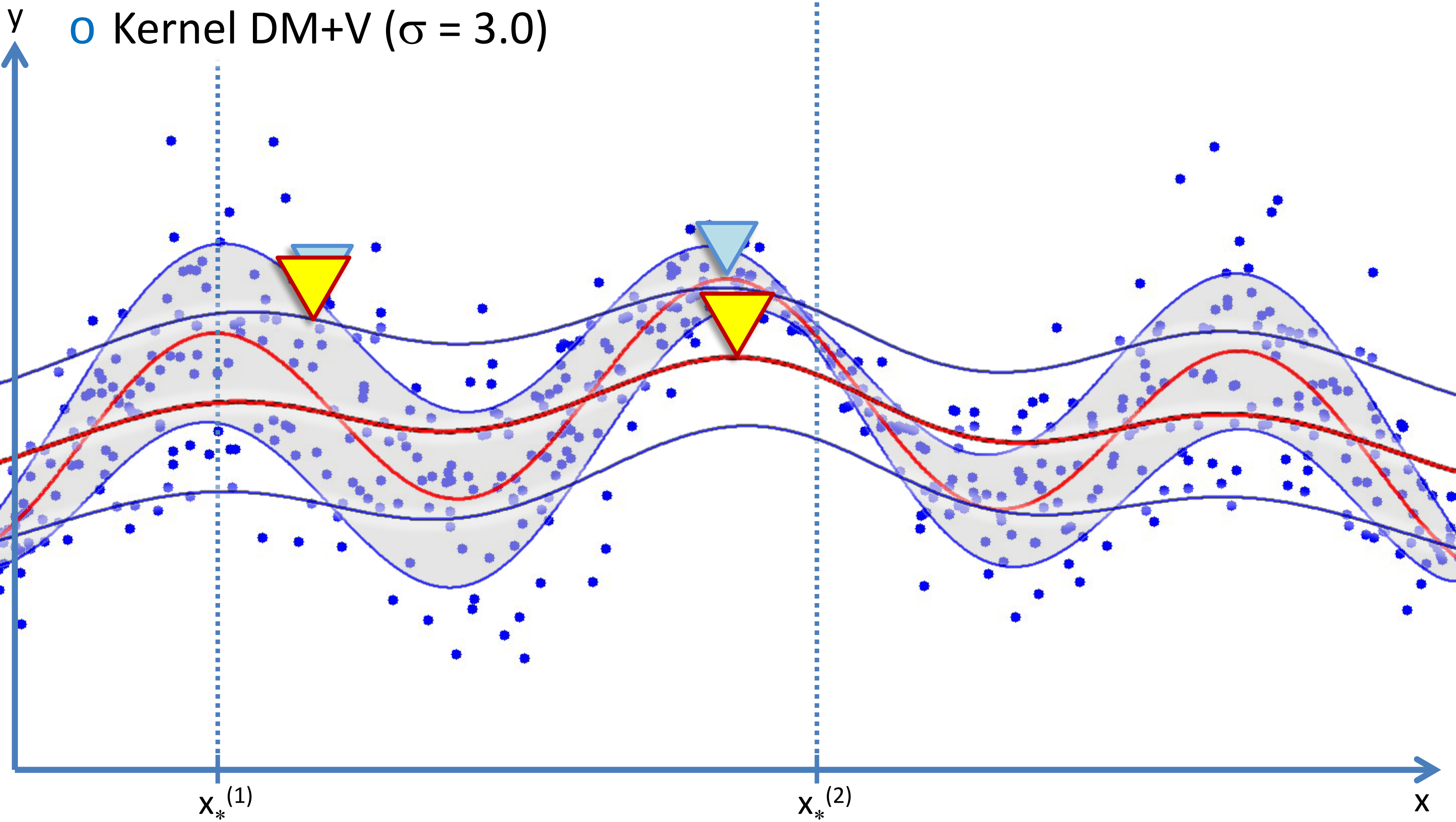


- **1D Example – Artificial Data (545 data points)**
  - Kernel DM+V (σ = 2.0)

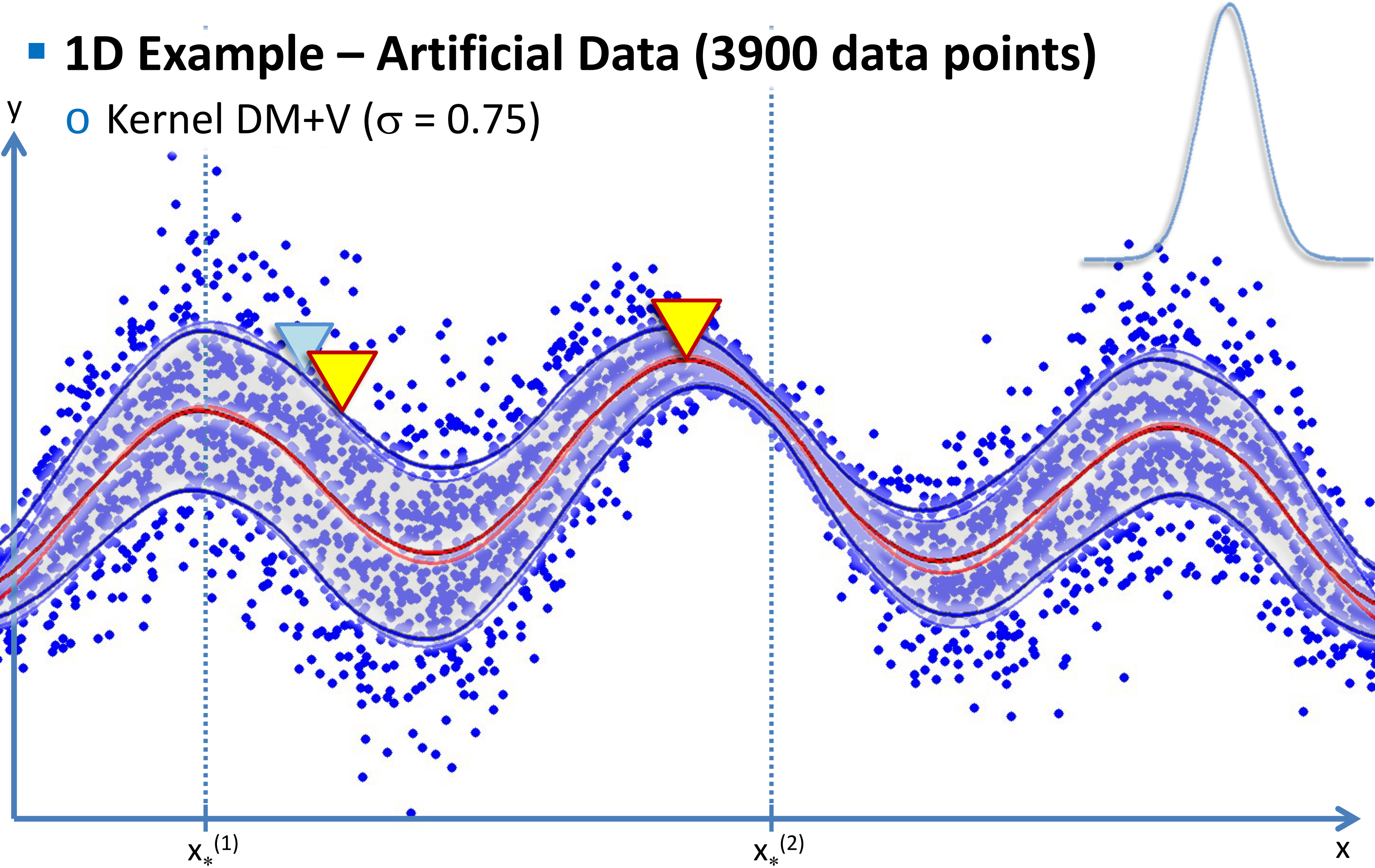


1D Example – Artificial Data (545 data points)

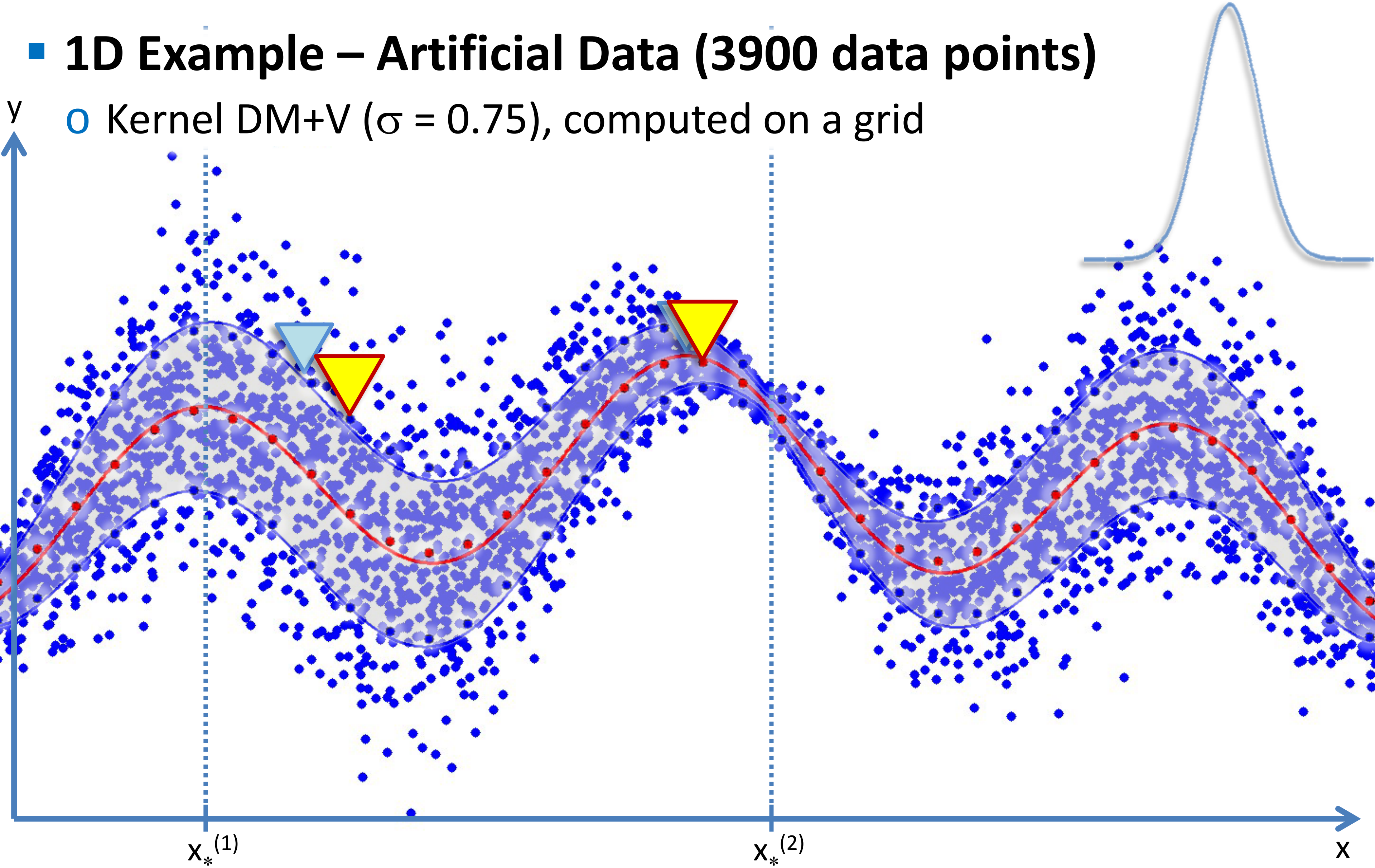
- Kernel DM+V (σ = 3.0)



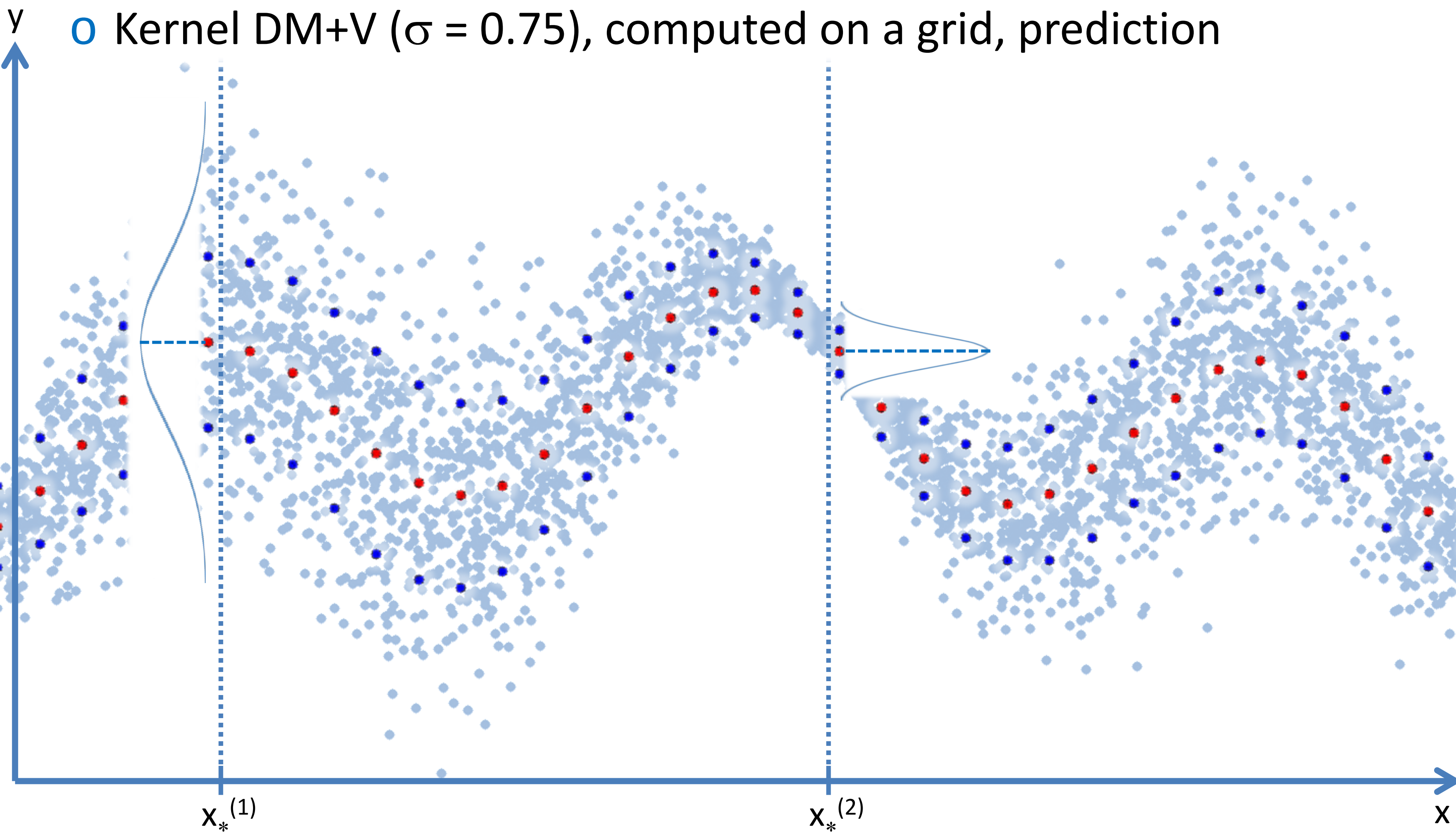
- **1D Example – Artificial Data (3900 data points)**
  - Kernel DM+V (σ = 0.75)



- **1D Example – Artificial Data (3900 data points)**
  - Kernel DM+V (σ = 0.75), computed on a grid

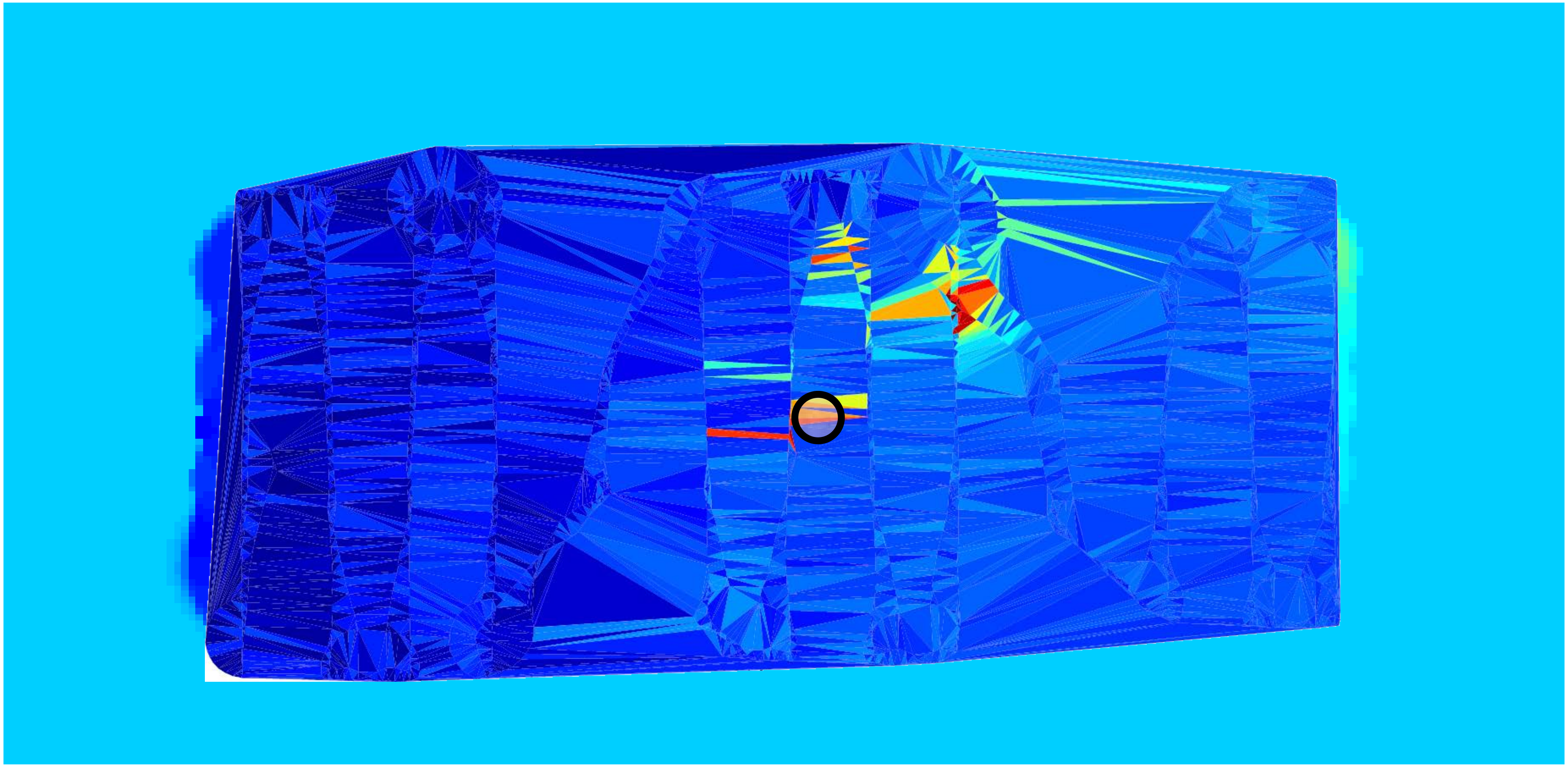


- **1D Example – Artificial Data (3900 data points)**
  - Kernel DM+V ($\sigma = 0.75$), computed on a grid, prediction

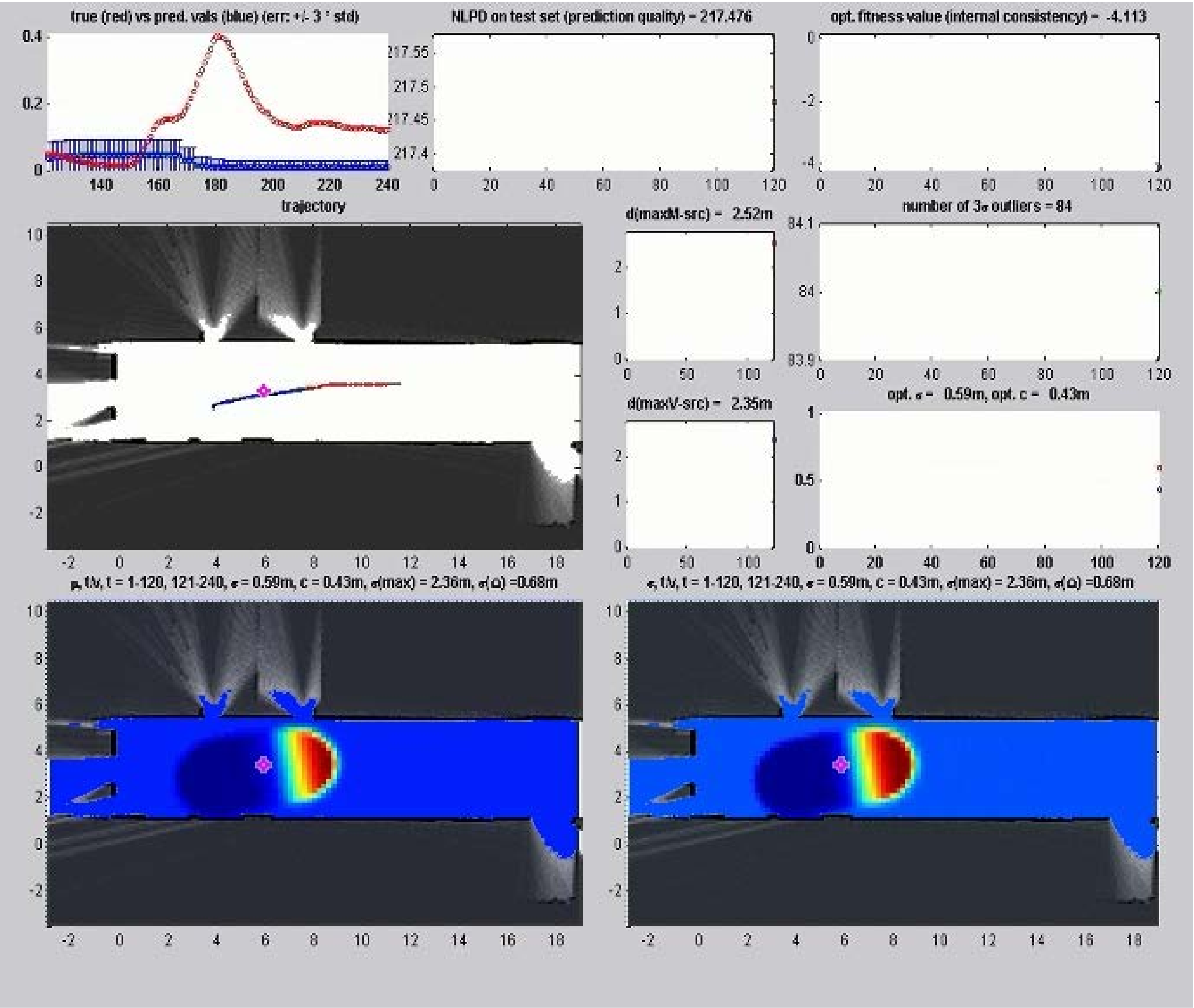


Kernel DM+V – Example

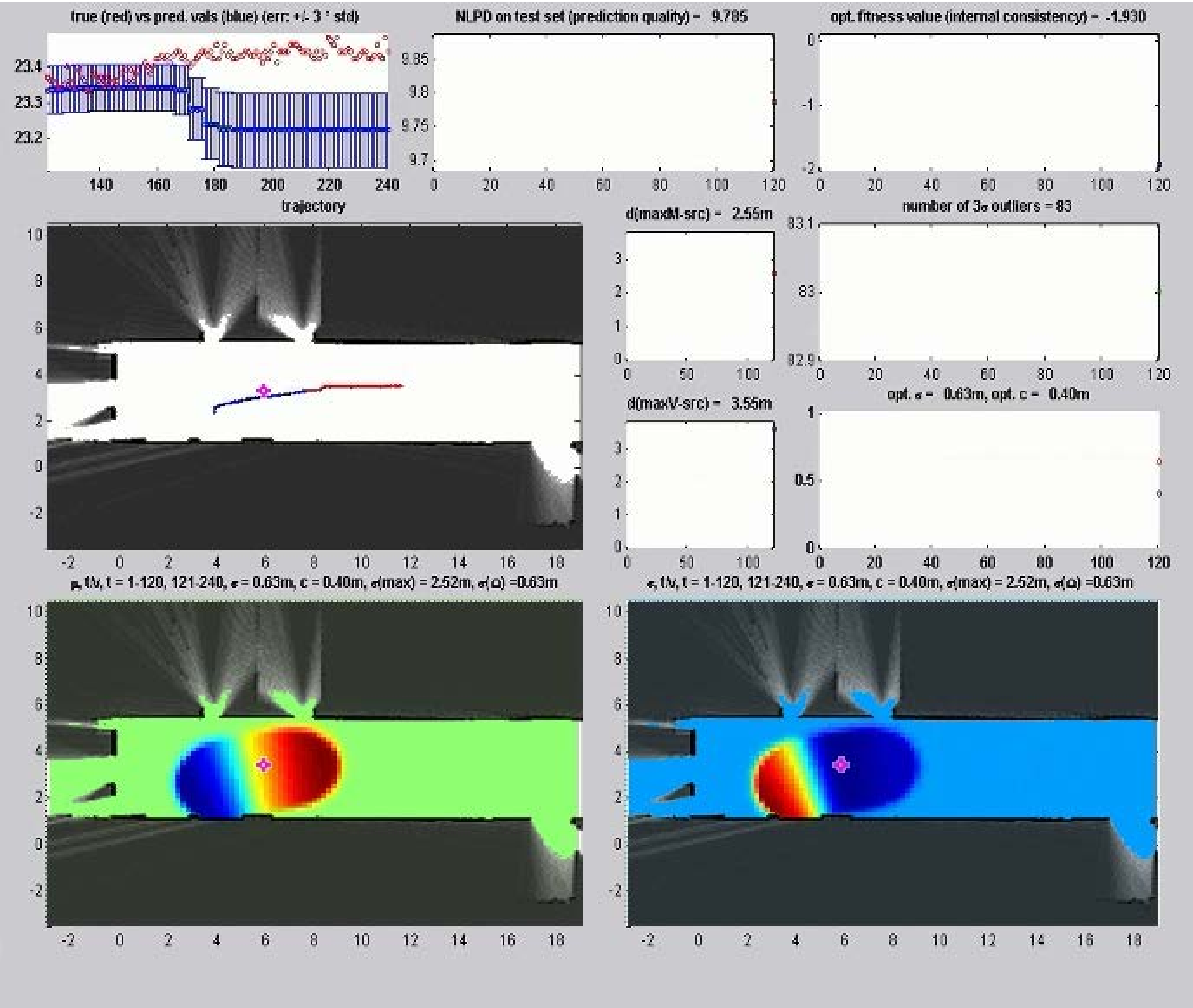
- Comparison with Map from Trilinear Interpolation (MATLAB function `trisurf`)



Kernel DM+V Example: Gas Distribution Map

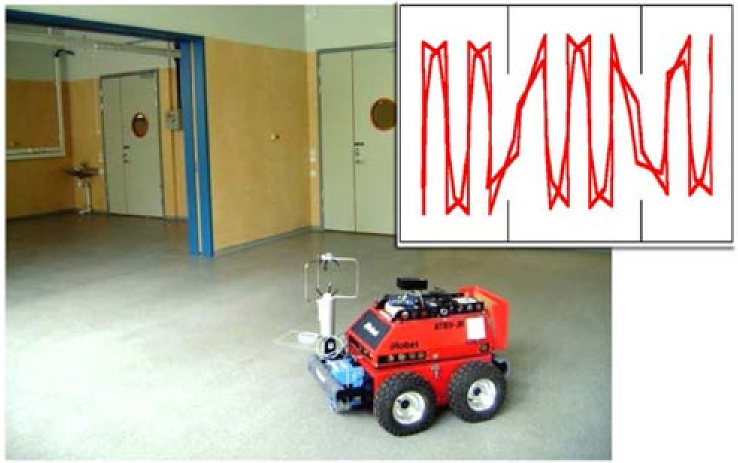


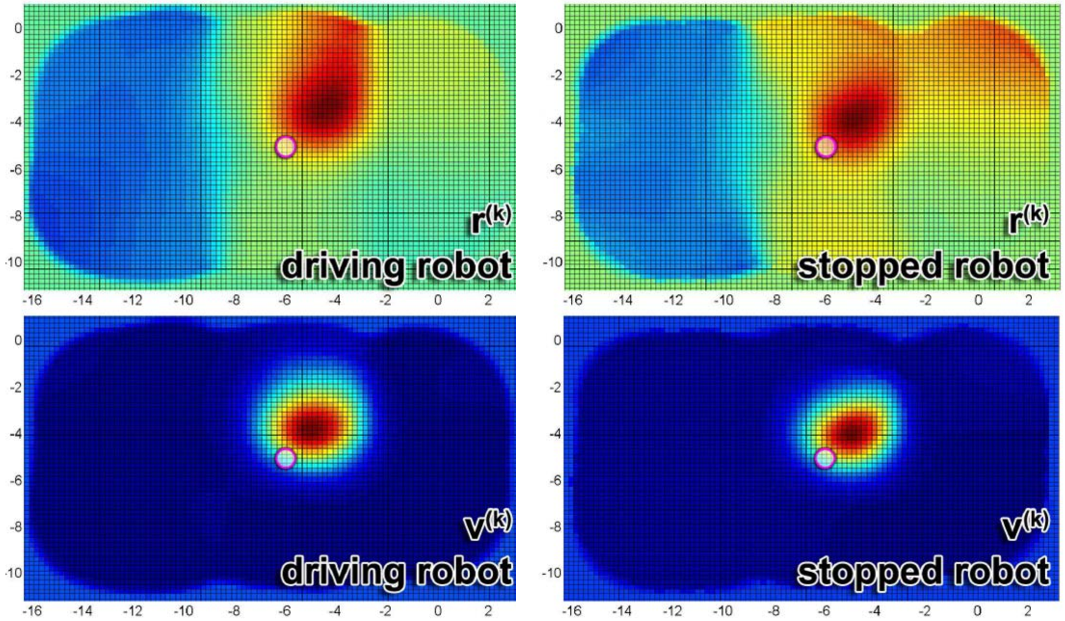
Kernel DM+V Example: Temperature Distribution Map



[Lilienthal et al., IROS 2009]

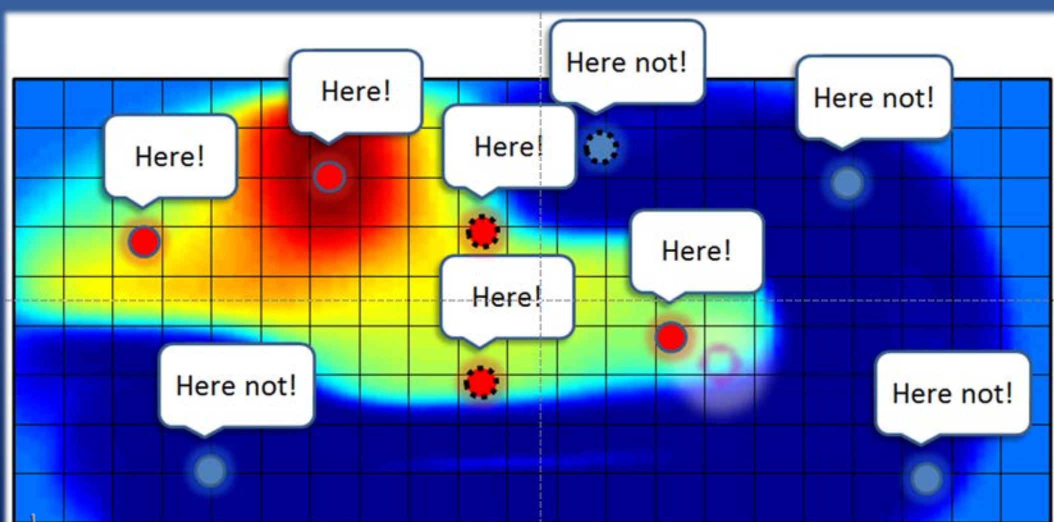
- **Gas Distribution Mapping**
  - Spatial mean <u>and</u> variance (Kernel DM+V)

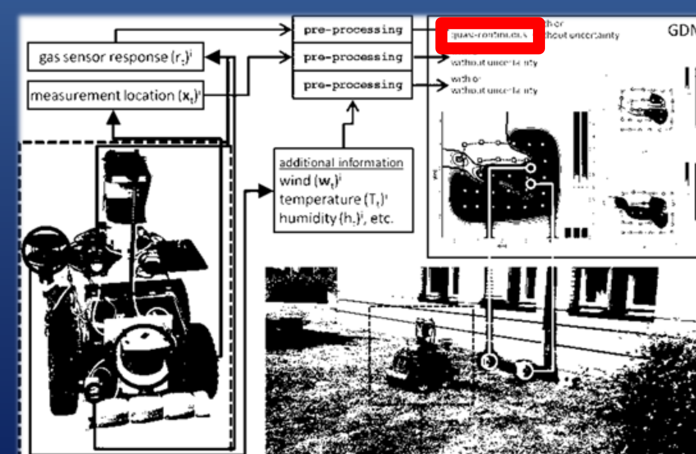




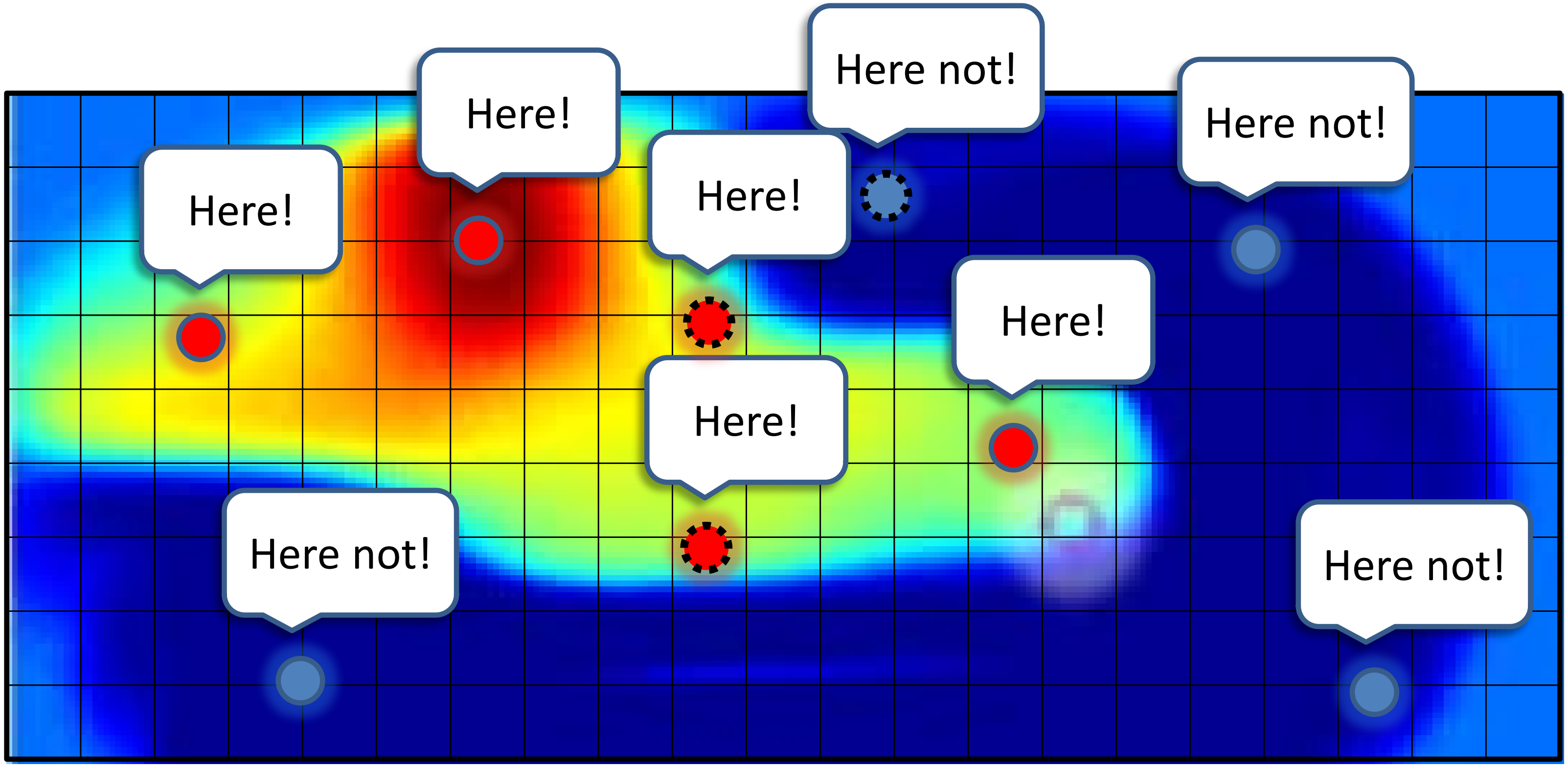
GDM with In Situ Sensors

Discrete Input (Binary)





- **Event Detection Distribution Maps**



Motivation

The DIADEM Project

[Asadi et al., EnviroInfo 2011]

- **DIADEM**
  - Distributed Information Acquisition and Decision-Making for Environmental Management

D-CIS LAB

DCMR milieudienst Rijnmond

BEREDSKABS STYRELSEN

spaceapplications SERVICES

ÖREBRO UNIVERSITET
Akademin för naturvetenskap och teknik

PROLOG DEVELOPMENT CENTER

THALES

Universität Karlsruhe (TH)

SOFTWARE sed ENGINEERING DEPARTMENT

Diadem

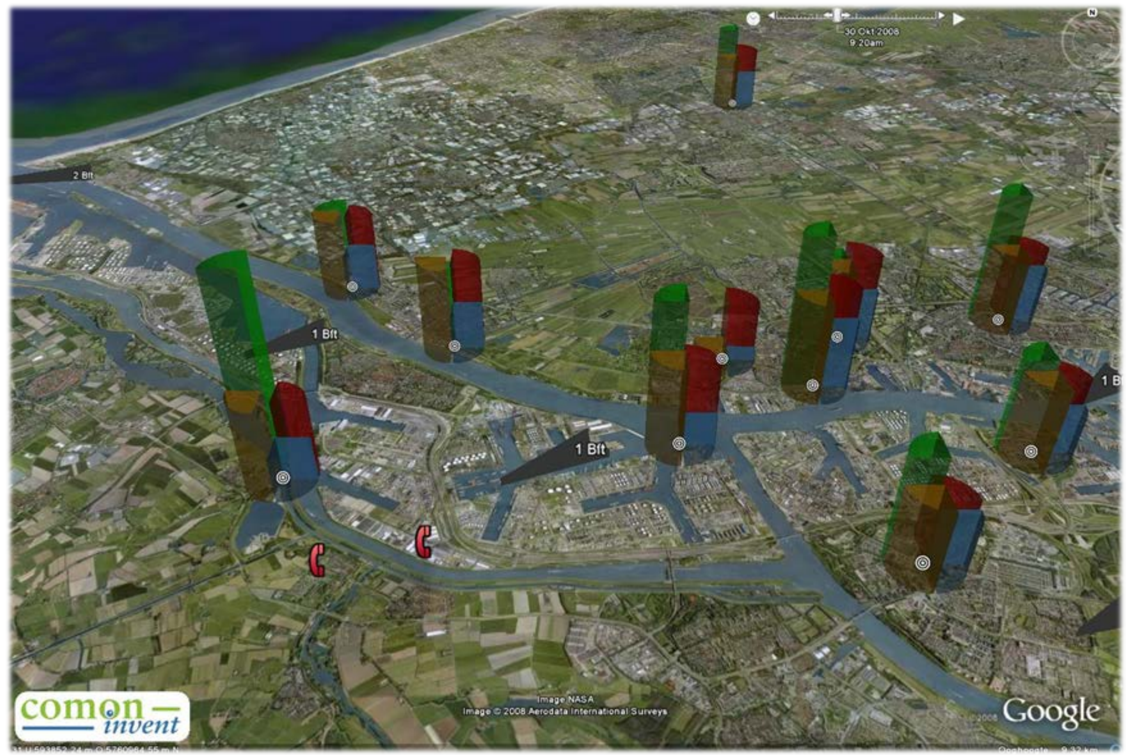
- **DIADEM**
  - Prime objective:
    "… create an ICT system for collaborative decision making that effectively supports the protection of the population and the environment against chemical hazards in industrial areas"

- **DIADEM**
  - Prime objective:
    "… create an ICT system for collaborative decision making that effectively supports the protection of the population and the environment against chemical hazards in industrial areas"
  - Addressed by developing
    - *"Advanced **gas detection and monitoring approaches** supporting enhanced situation awareness"*
    - *"Advanced human machine interfaces supporting efficient exploitation of human cognitive capabilities"*
    - *"Methods and tools facilitating collaborative decision making (large scale collaborative decision making processes involving multiple, geographically distributed organizations)*

Online Pollution Monitoring, Rijnmond Area

- 11 sensor stations
  - 4 MOX sensors each
  - Temperature and humidity sensor

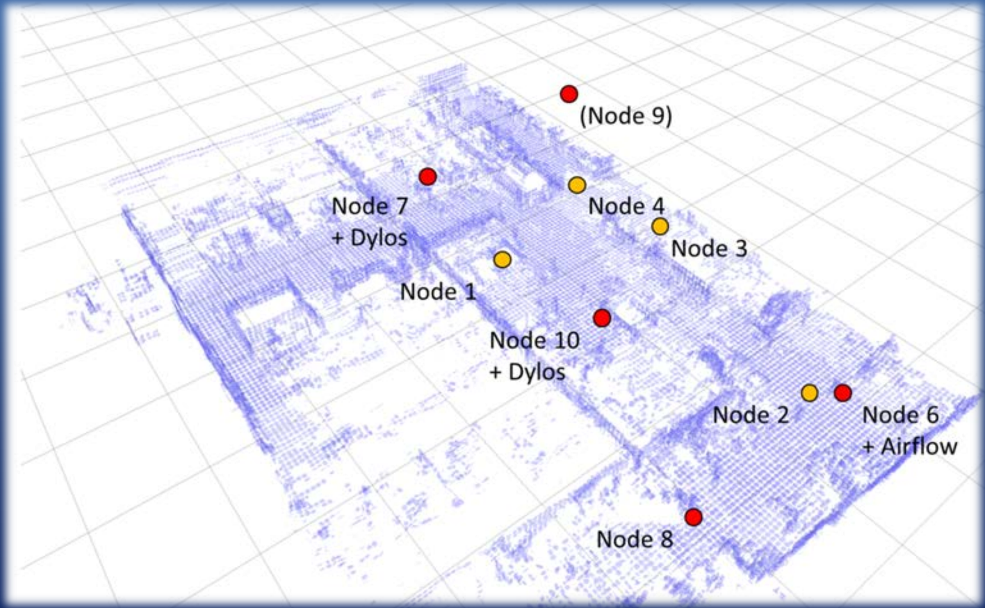
- **Particular Challenges**
  - Large scale, sparse measurements
  - Un-calibrated data



- **Particular Challenges**
  - Large scale, sparse measurements
  - Un-calibrated data
  - Merging of human reports (localized complaints)
    - Gas detection
    - Gas distribution modelling

Robot Supported Air Quality Monitoring Sensor Networks

From Foundries to Urban Sensing



- **KKS Project RAISE**
  - o Example: Measurement Camping at Foundry

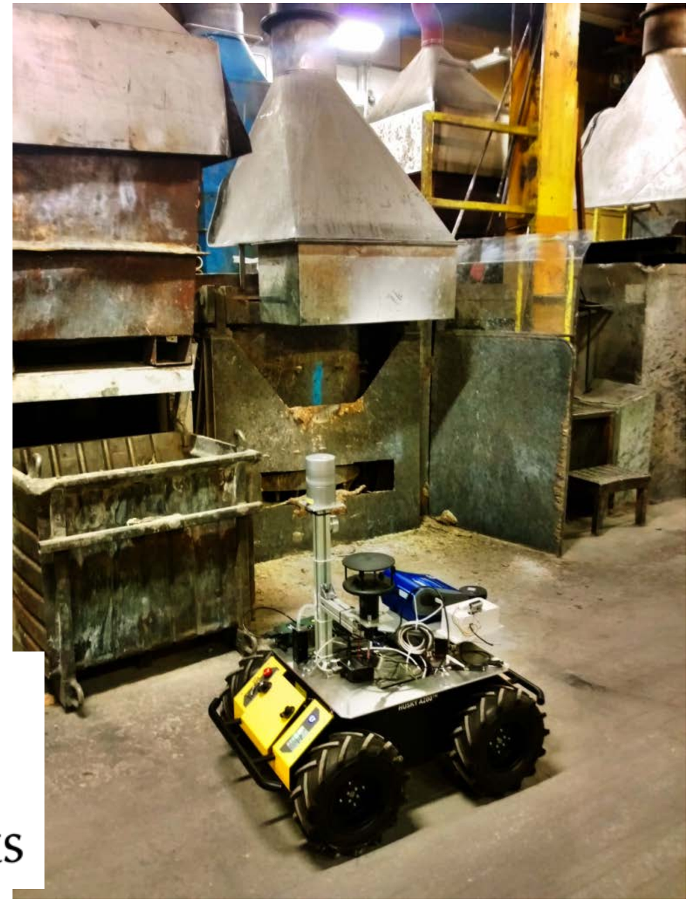
[Hernandez Bennets et al., IROS 2016]

Region Örebro län
Arbets- och miljömedicin

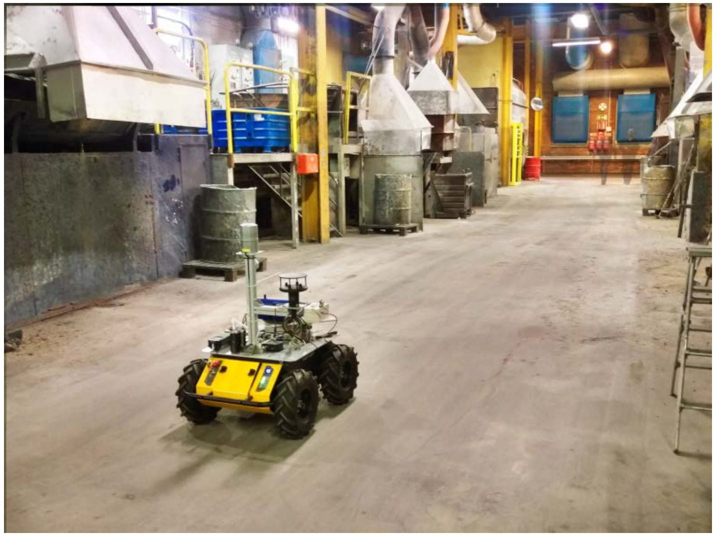
Global Castings
GULDSMEDSHYTTAN

JOHNSON METALL AB

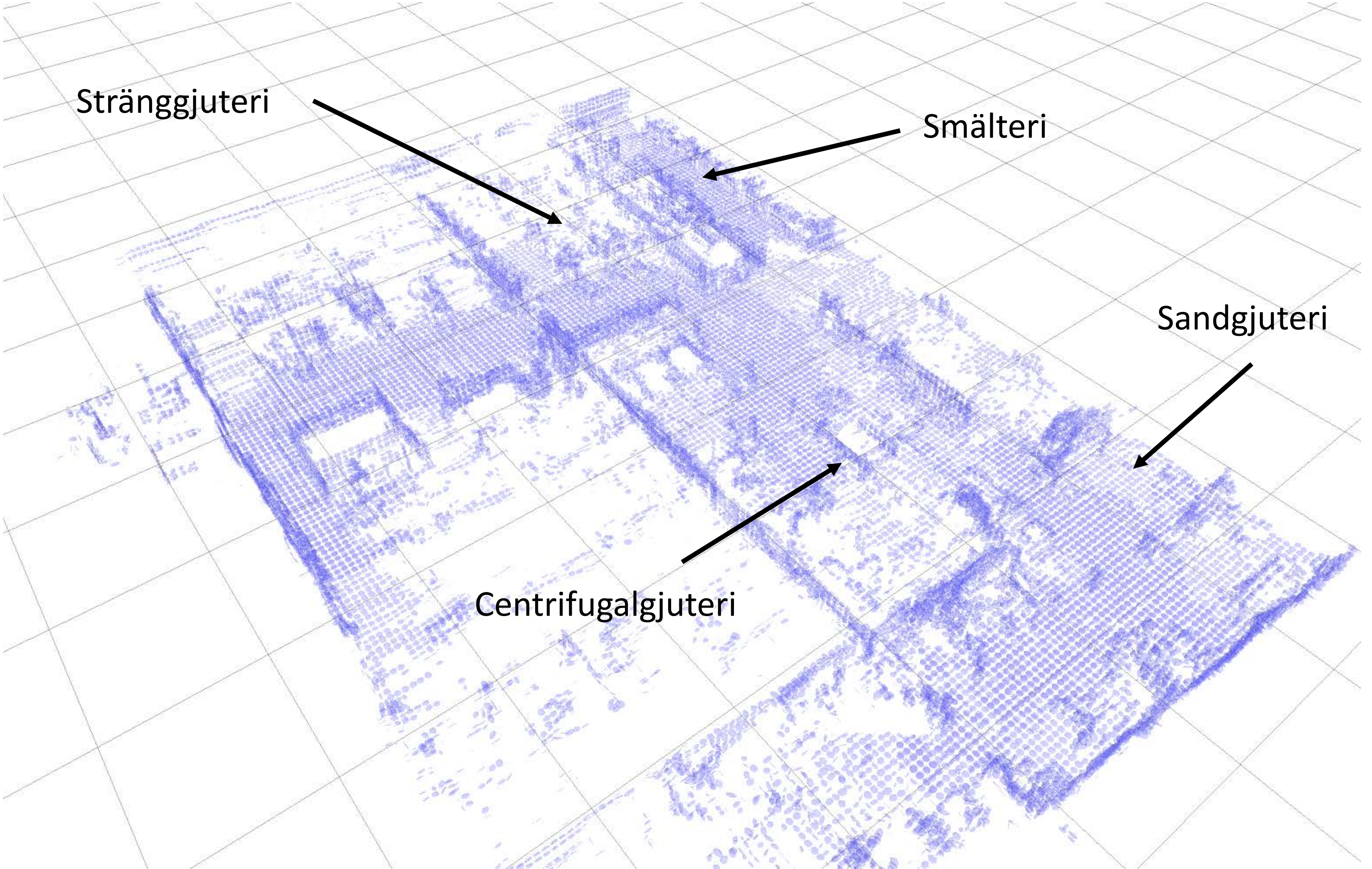
RAISE
Robotic System for Air Quality Assessment in Industrial Environments



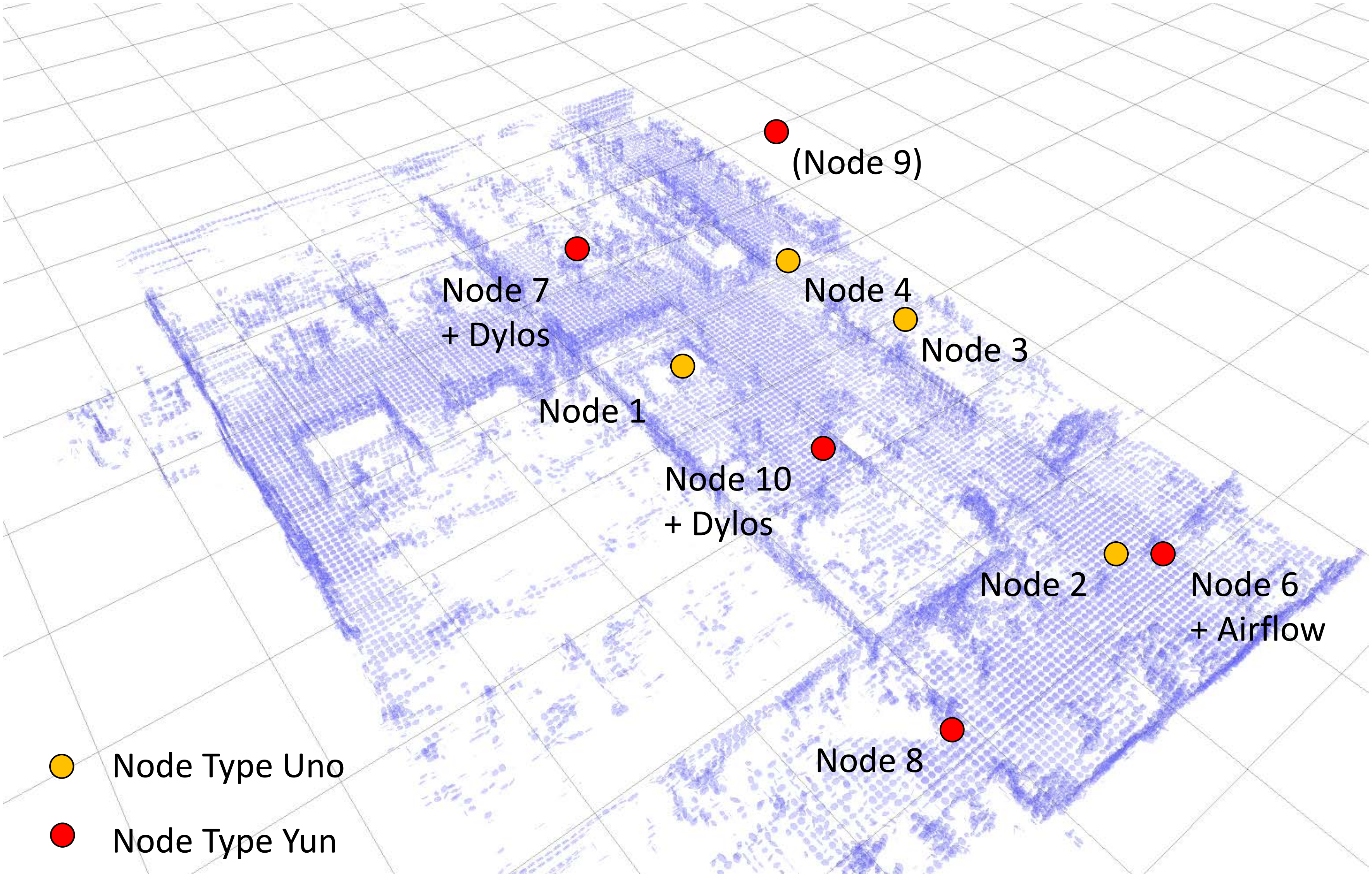
KKS Project RAISE, Measurement Camping at Foundry



- **KKS Project RAISE, Measurement Camping at Foundry A**
  - Robot builds 3D map of the environment

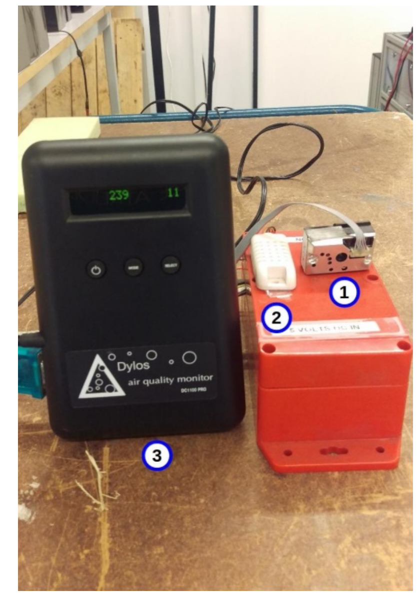


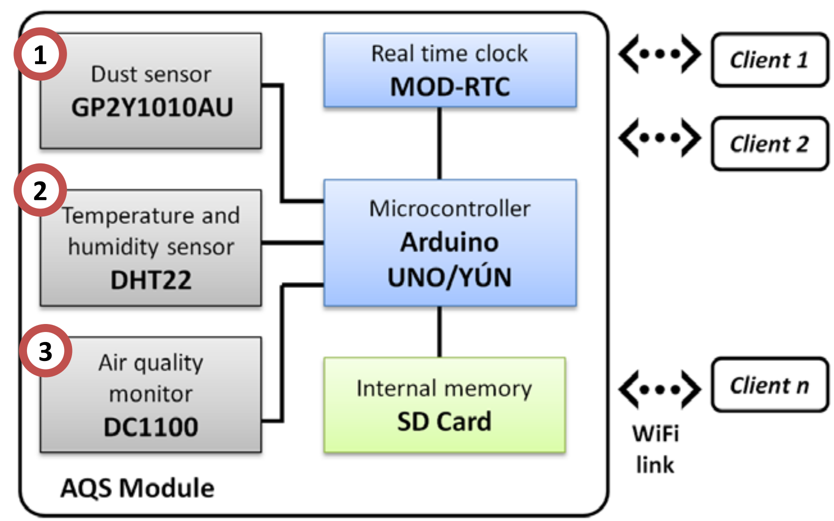
- **KKS Project RAISE, Measurement Camping at Foundry A**
  - Long-term deployment since October 2015



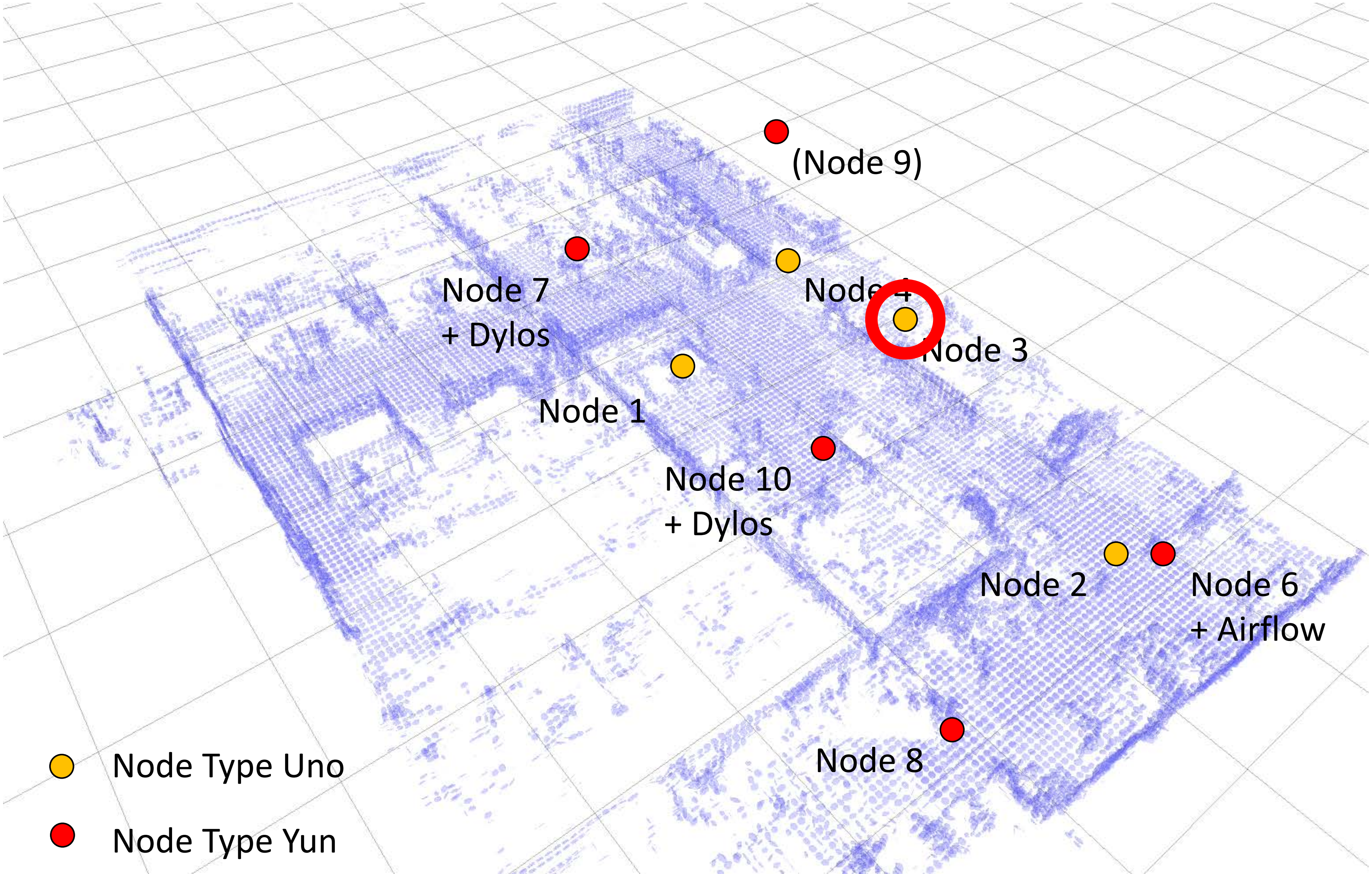
Air Quality Sensing Modules (AQSMs)

- In-situ sensors@1Hz
  - Dust concentration (GP2Y1010AU)
    - Inexpensive PM sensor
    - Optical dust sensor for detection of fine airborne particles (e.g. dust, smoke), mass density resolution = 0.1 mg/m^3
  - Temperature/humidity sensor (DHT22)
- Additions for a few nodes (Yun)
  - Air quality (DC1100)
    - PM25 and PM10
    - Expensive PM sensor
  - 3D anemometer
- Data storage
  - Inside the sensor on a SD card
  - Accesible via external WiFi queries

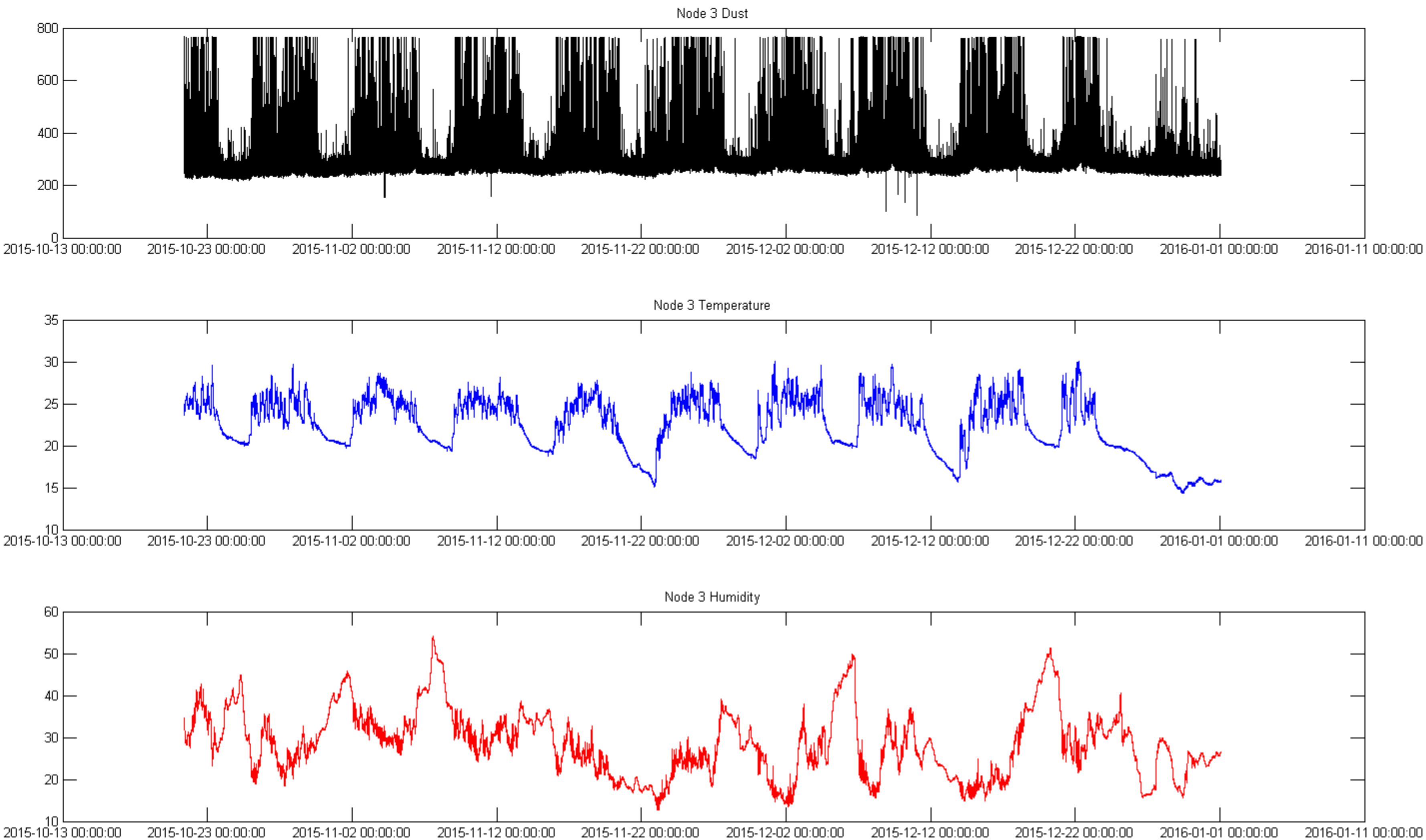




- **KKS Project RAISE, Measurement Camping at Foundry A**
  - Long-term deployment since October 2015

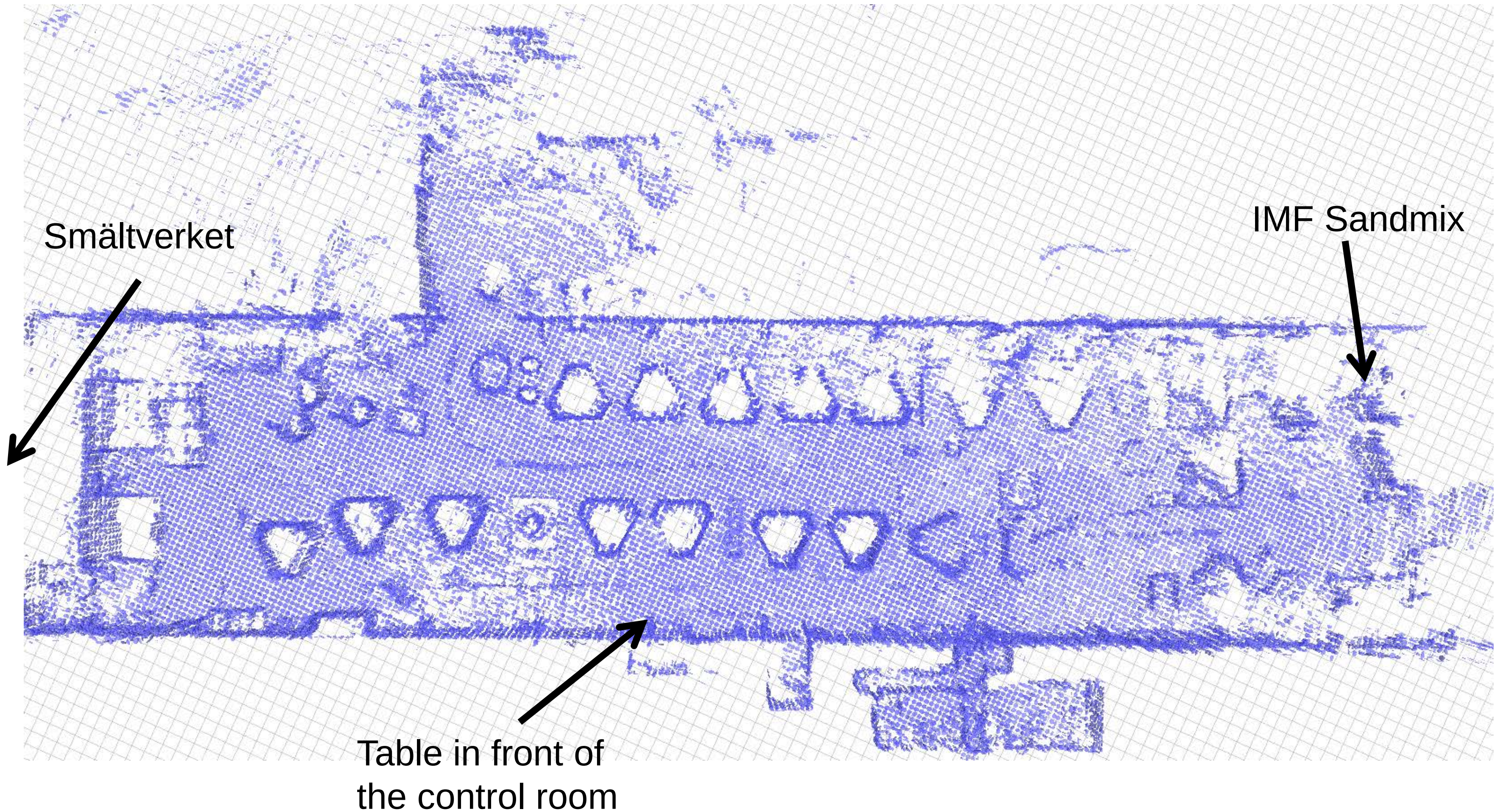


- **KKS Project RAISE, Measurement Camping at Foundry A**
  - Long-term deployment since October 2015
    - Node 3: Oct 17 – Dec 31, 2015 (5.378.277 measurements)

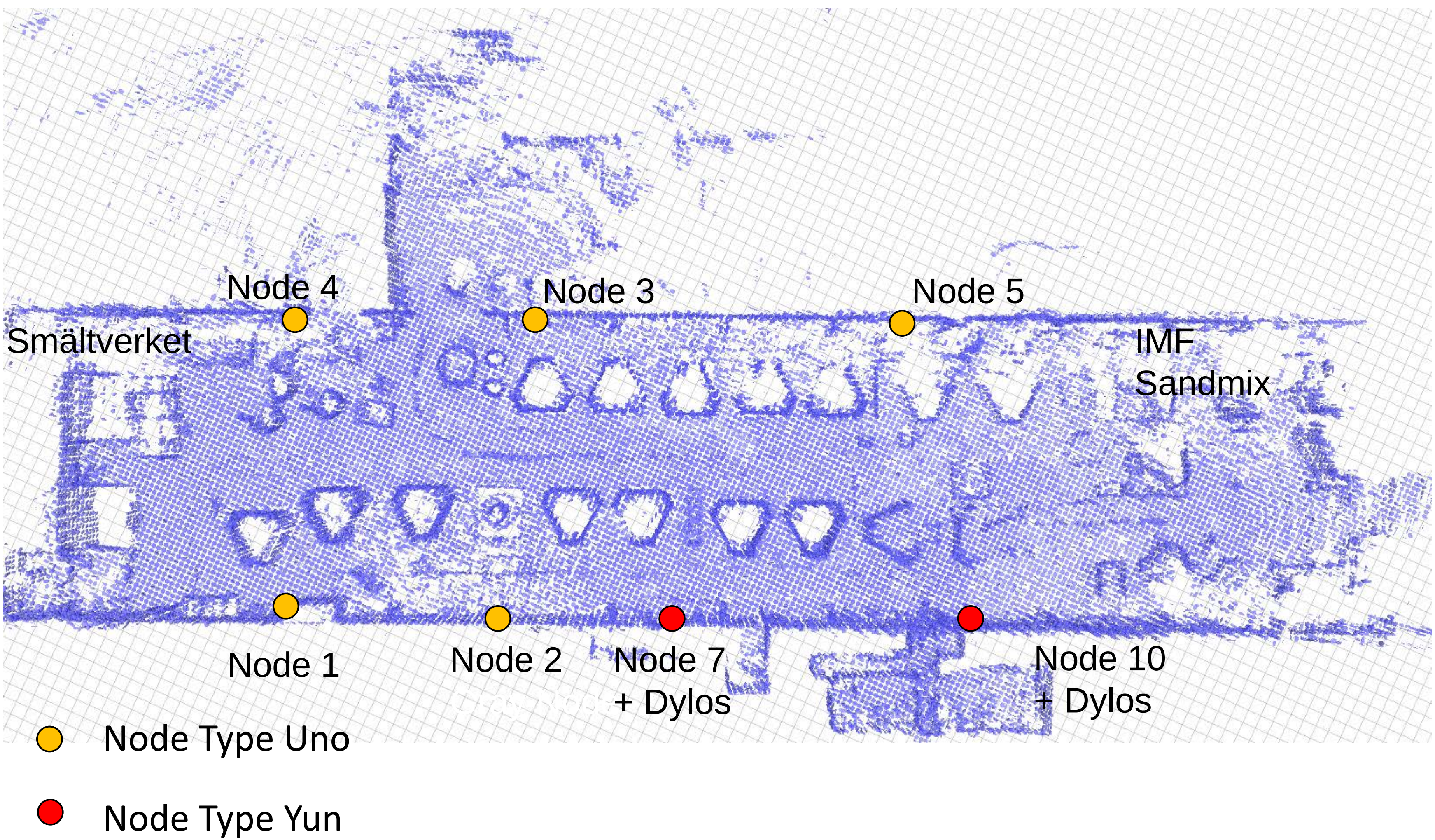


- **KKS Project RAISE, Robots to Improve Interpolation**

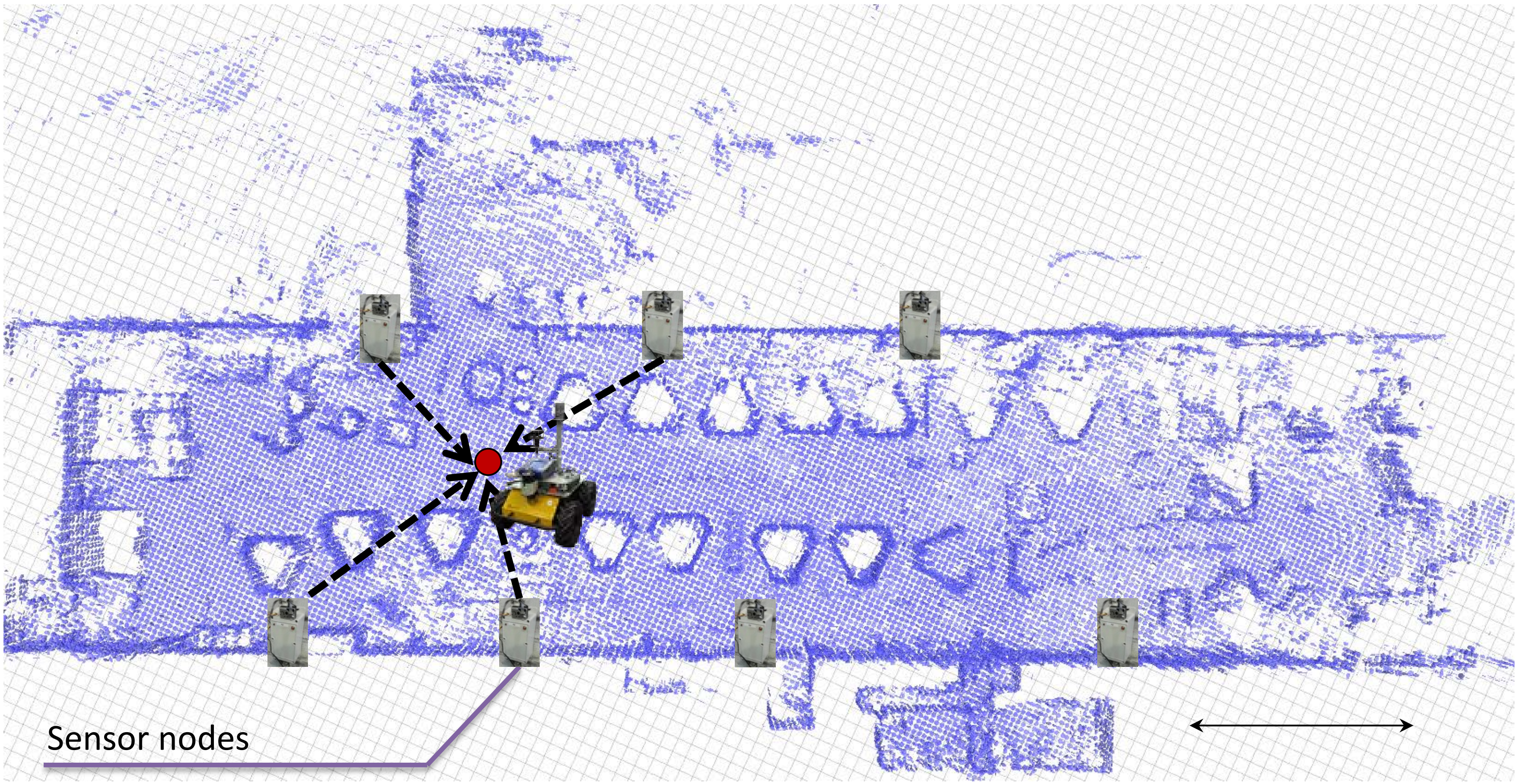
- **KKS Project RAISE, Measurement Camping at Foundry B**
  - Long-term deployment from June 2015 until September 2015



- **KKS Project RAISE, Measurement Camping at Foundry B**
  - Long-term deployment from June 2015 until September 2015

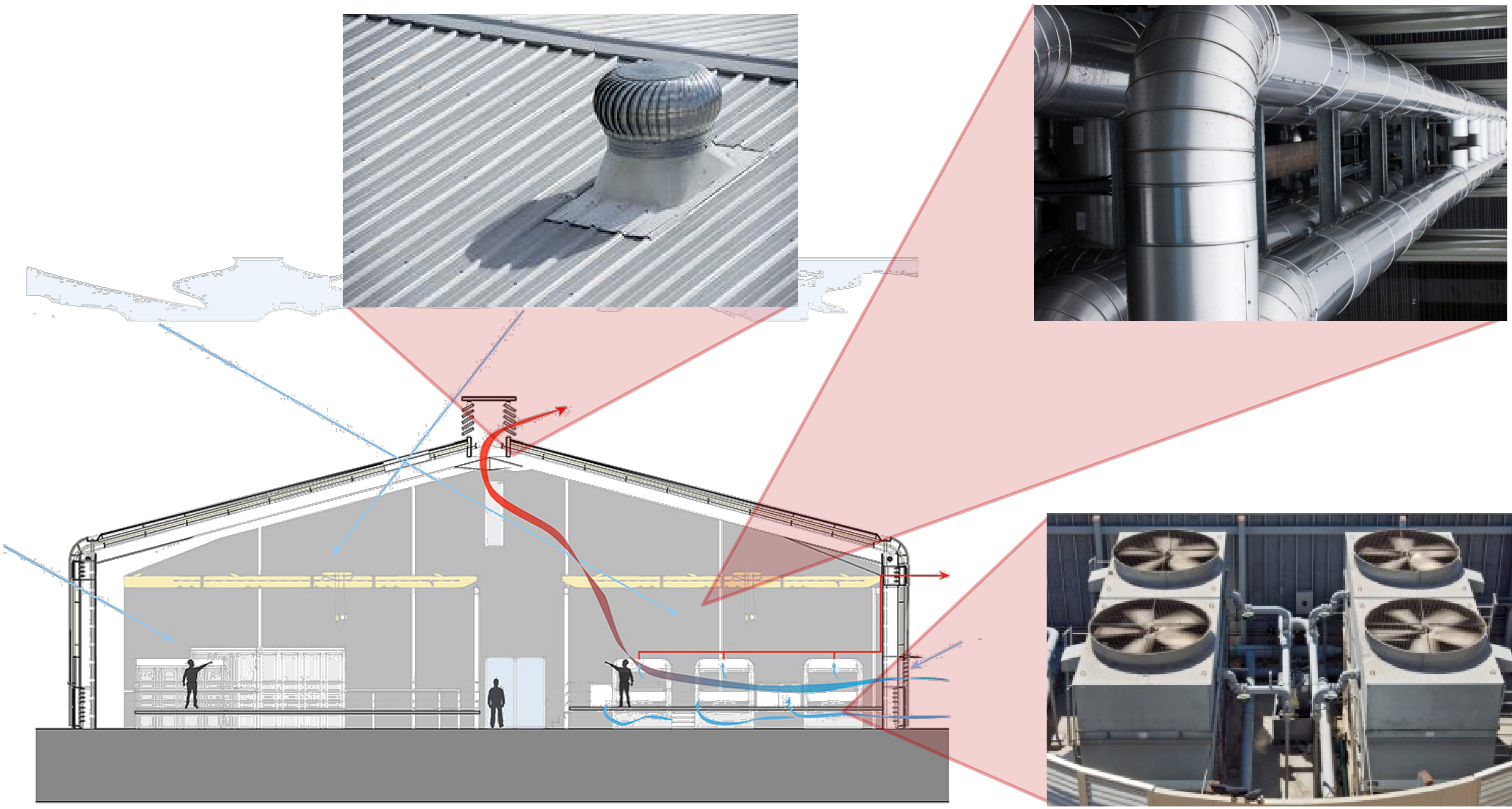


- **KKS Project RAISE, Robots to Improve Interpolation**
  - Idea: Derive model of interpolation between sensor nodes, calibrated with robot measurements



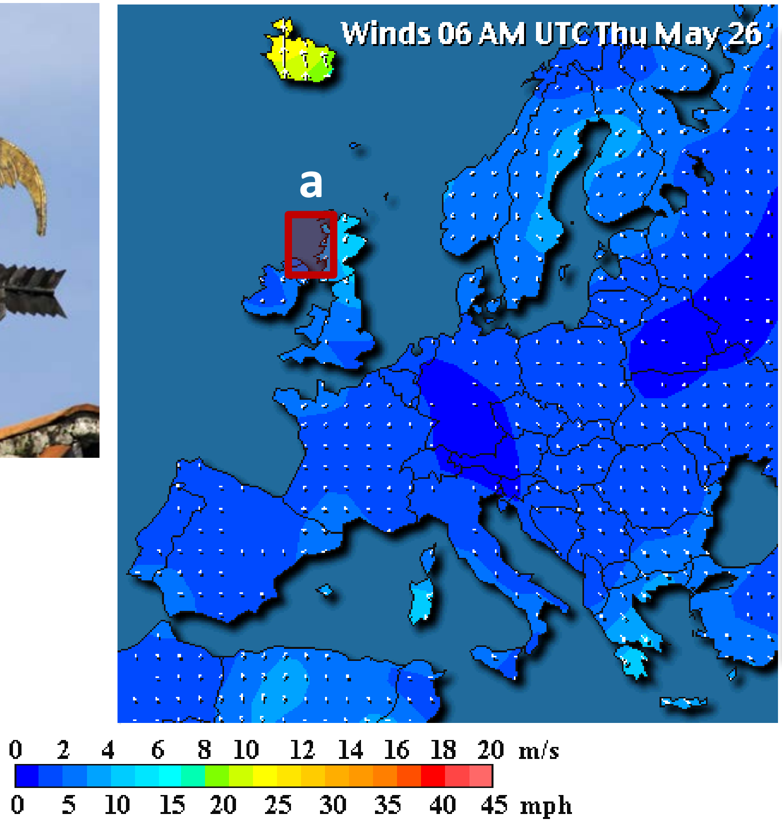
- **KKS Project RAISE, Airflow Mapping**
  - Airflow affects pollutant distribution (in a work environment)

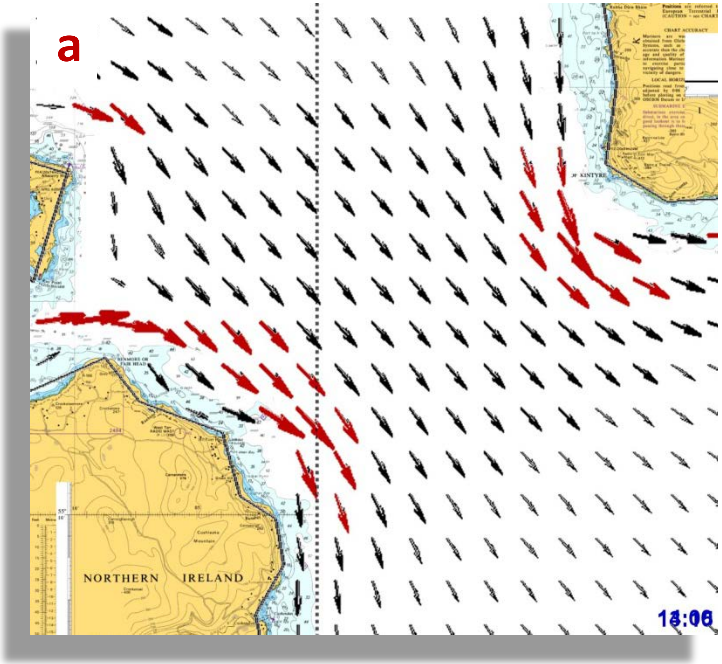
- **KKS Project RAISE, Airflow Mapping**
  - Pollutants are diluted and displaced by air streams produced by the in-place ventilation system
    - Fans, gates, exhaust ports, heating/cooling devices



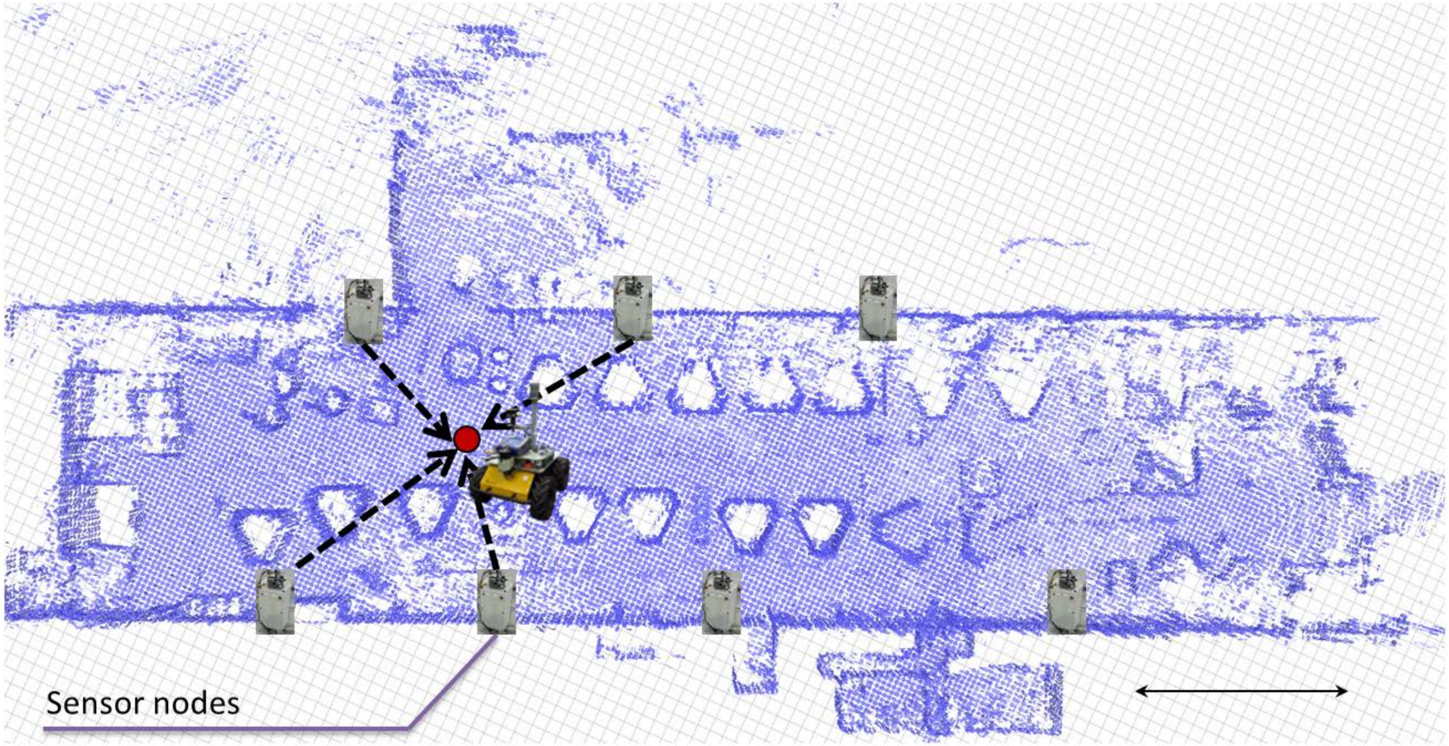
KKS Project RAISE, Airflow Mapping

- Analogous to weather forecasting, RAISE aims to create maps that
  - Model the airflow from acquired data (data-driven)
  - Show the distribution of airstreams in **indoor** environments
  - Predict local wind speed/direction information at query locations
  - Can help to understand how the ventilation system works





- **KKS Project RAISE, Airflow Mapping**
  - Analogous to weather forecasting, RAISE aims to create maps that
    - » Model the airflow from acquired data (data-driven)
    - » Show the distribution of airstreams in **indoor** environments
    - » Predict local wind speed/direction information at query locations
    - » Can help to understand how the ventilation system works
  - Can help to derive model of interpolation between sensor nodes

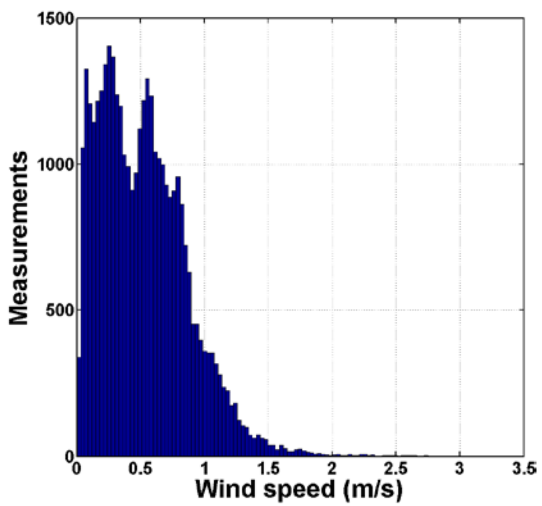


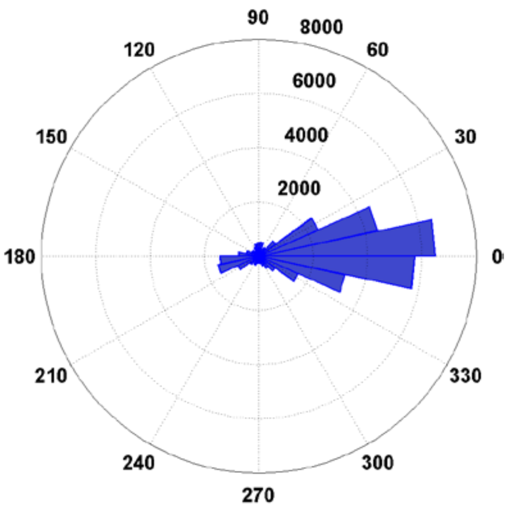
- **KKS Project RAISE, Airflow Mapping**

- **KKS Project RAISE, Robot Airflow Mapping**
  - Estimating airflow velocity fields field using mobile robots

KKS Project RAISE, Robot Airflow Mapping

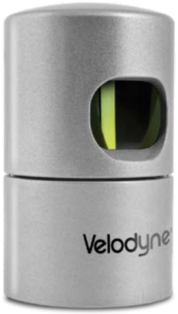
- Estimating airflow velocity fields field using mobile robots
  - 2-D Gill Windsonic Anemometer
    - Wind speed: 0-60m/s, 0.02m/s resolution
    - Wind direction: 0-360°, 1° resolution

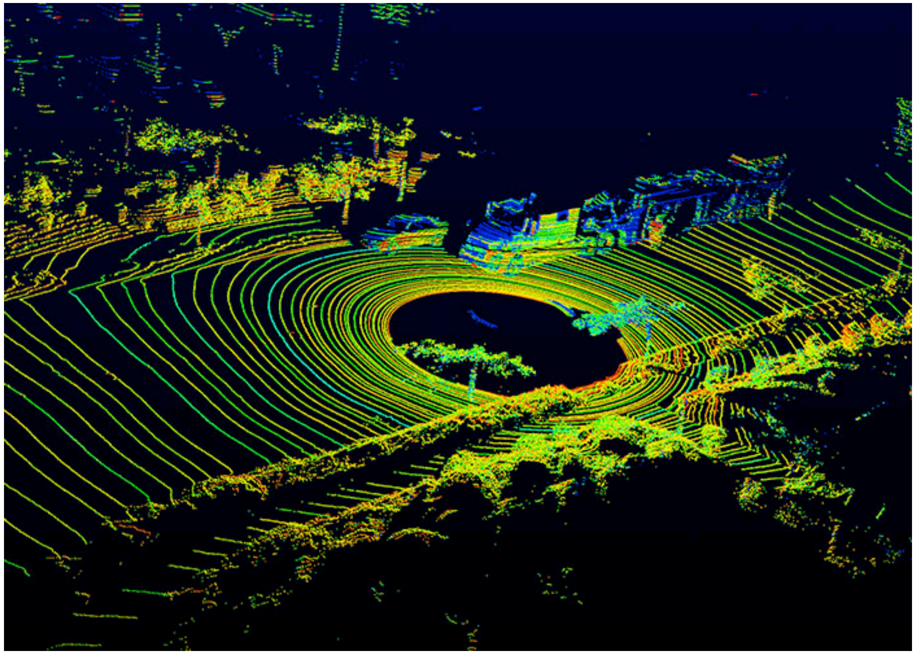




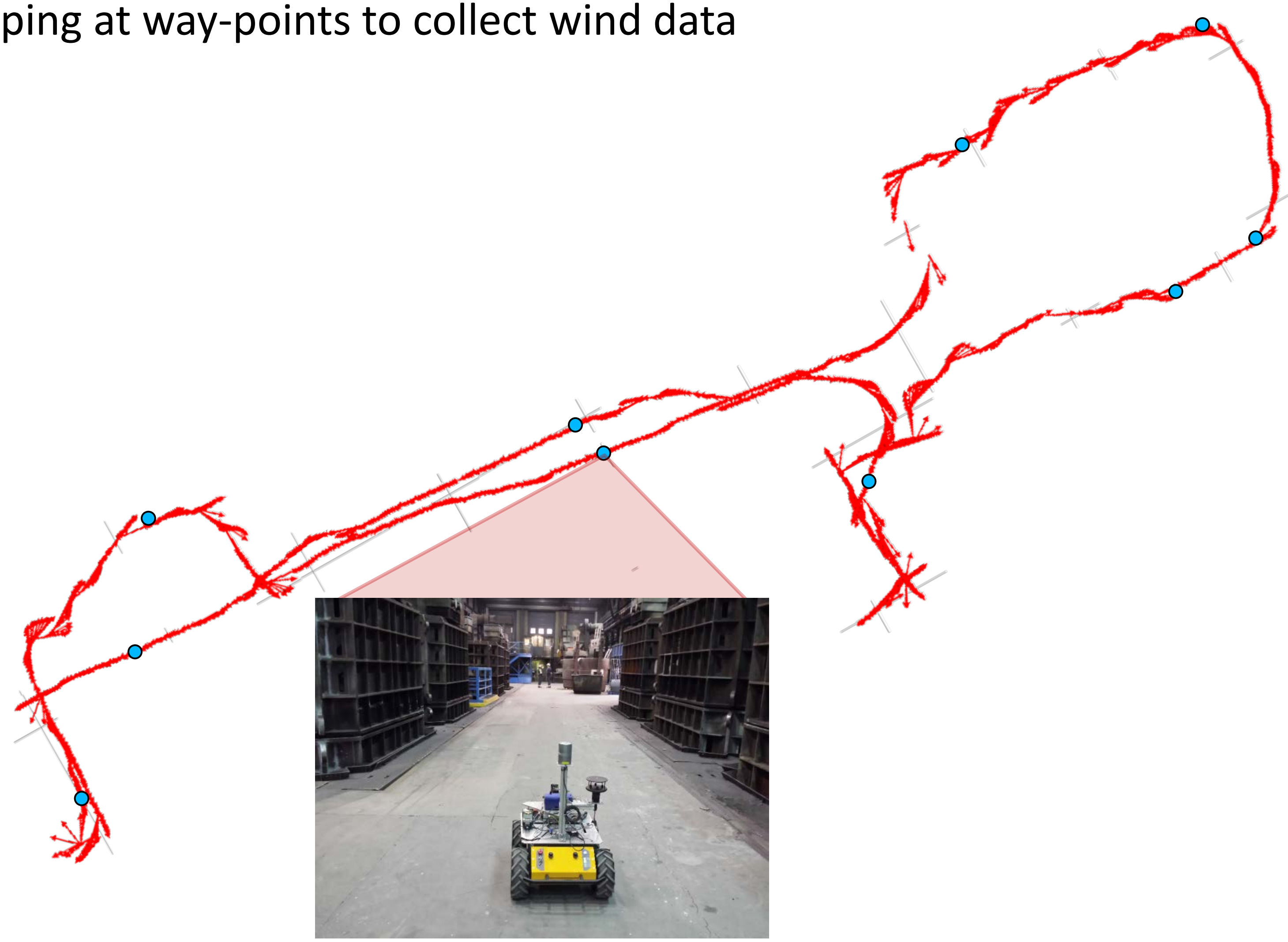
KKS Project RAISE, Robot Airflow Mapping

- Estimating airflow velocity fields field using mobile robots
  - HDL32-E 3-D Range sensor
    - 360° field of view
    - Up to 100m range
    - 700,000 points per second

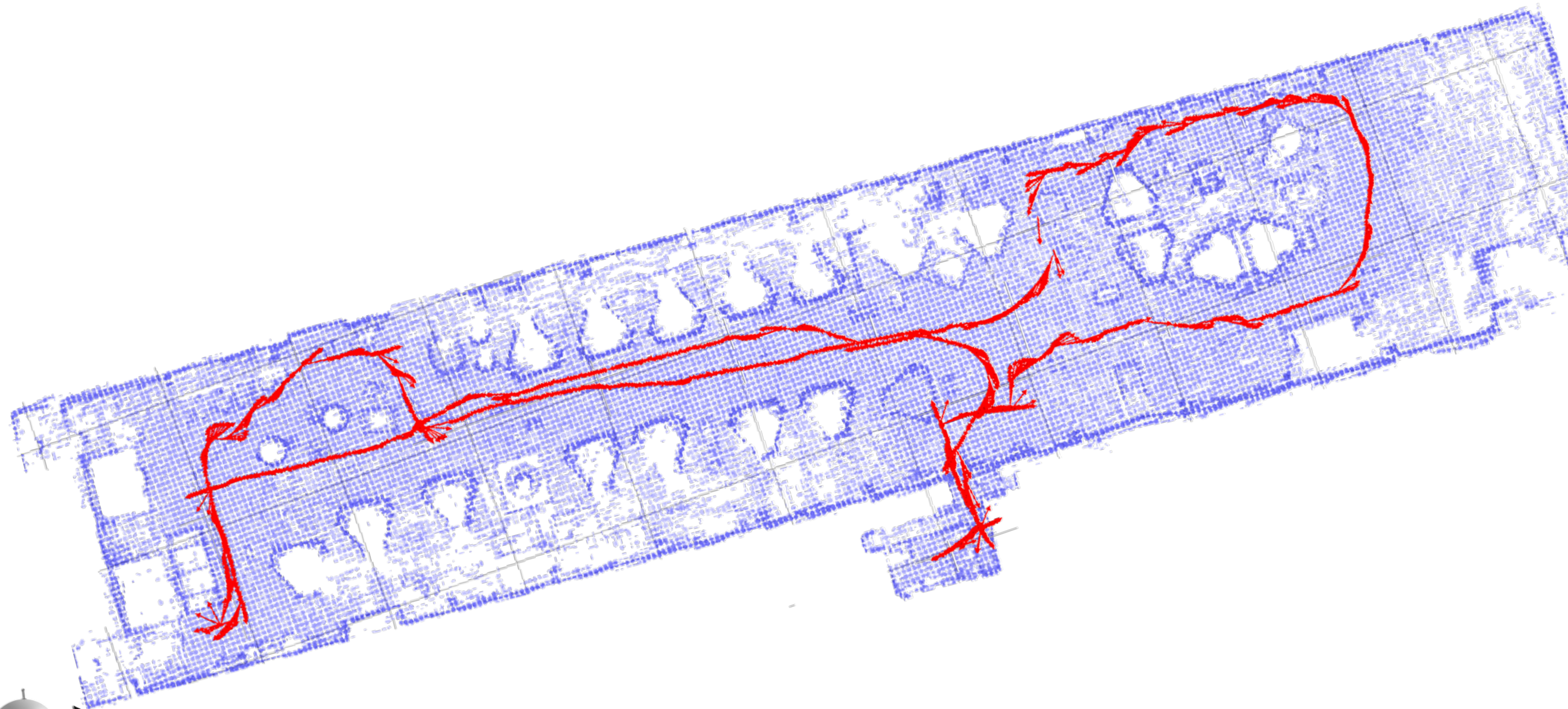




- **KKS Project RAISE, Robot Airflow Mapping Process**
  - (1) Robot is driven to inspect the facility
    - Stopping at way-points to collect wind data

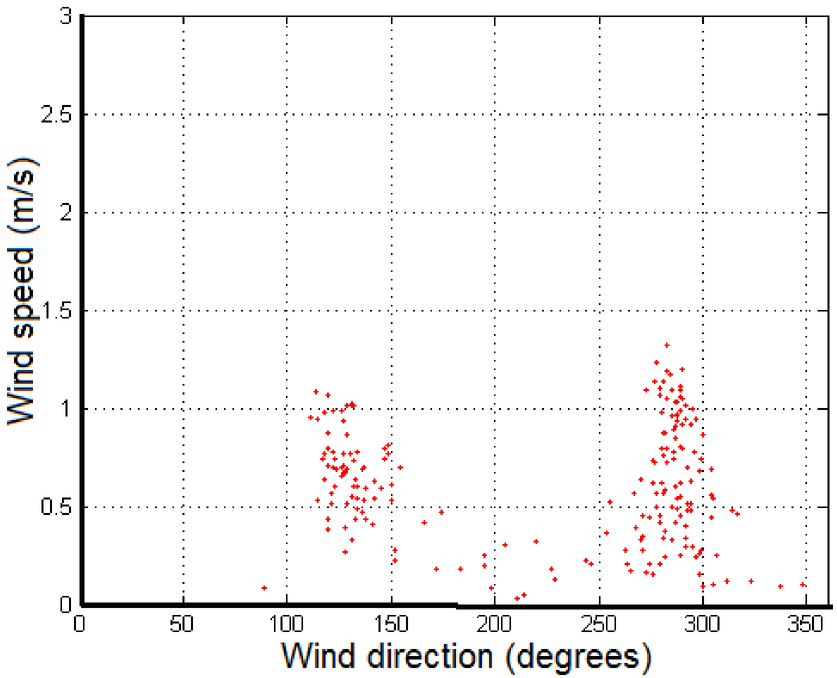


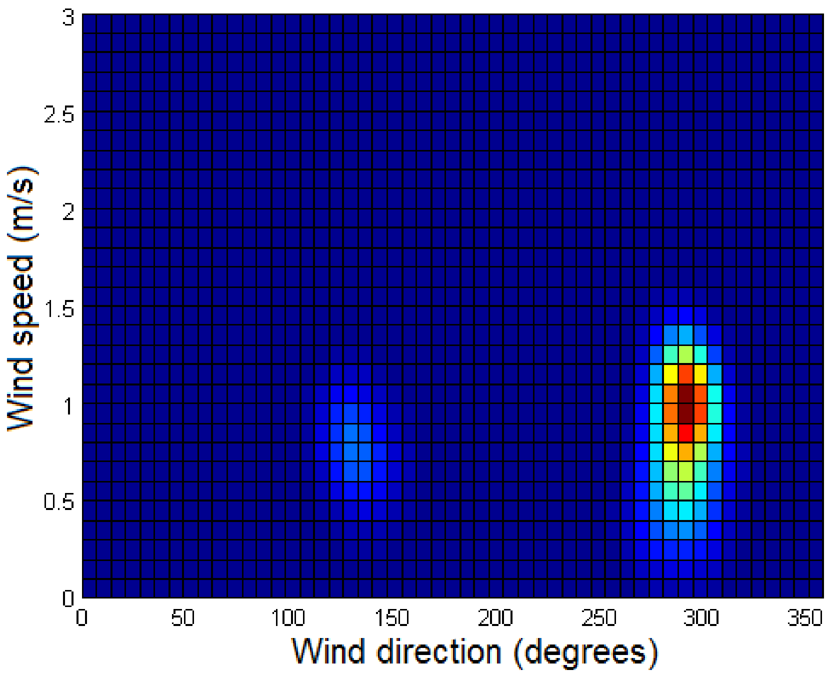
- **KKS Project RAISE, Robot Airflow Mapping Process**
  - (2) Estimate geometrical model from range measurements



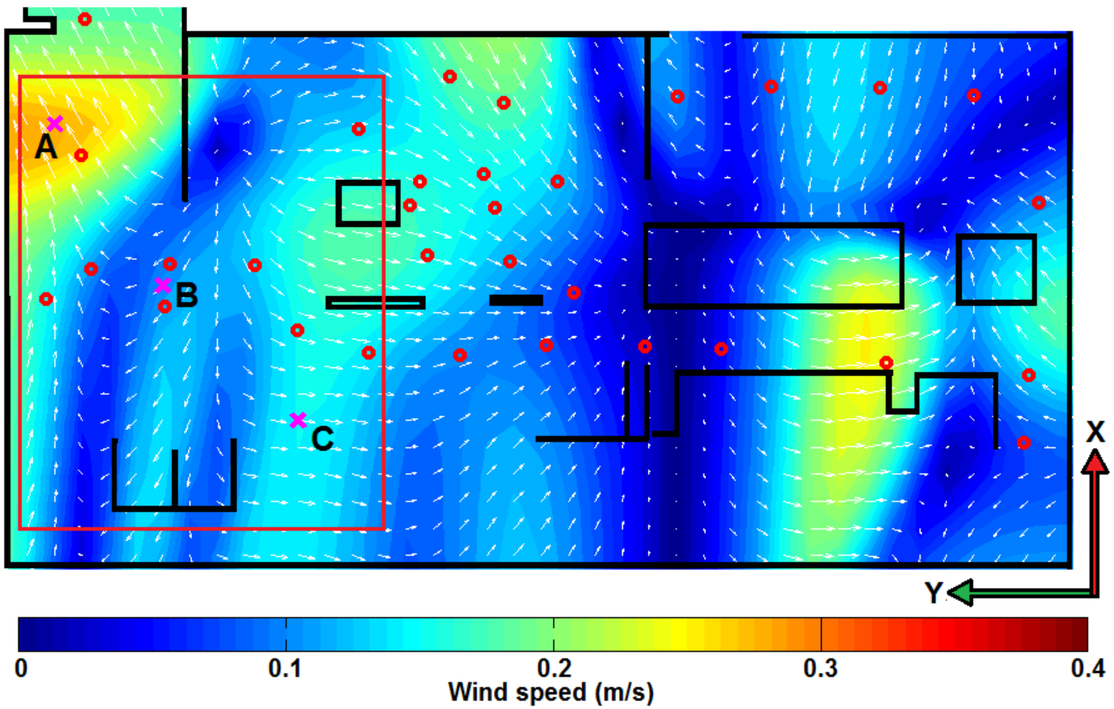
KKS Project RAISE, Robot Airflow Mapping Process

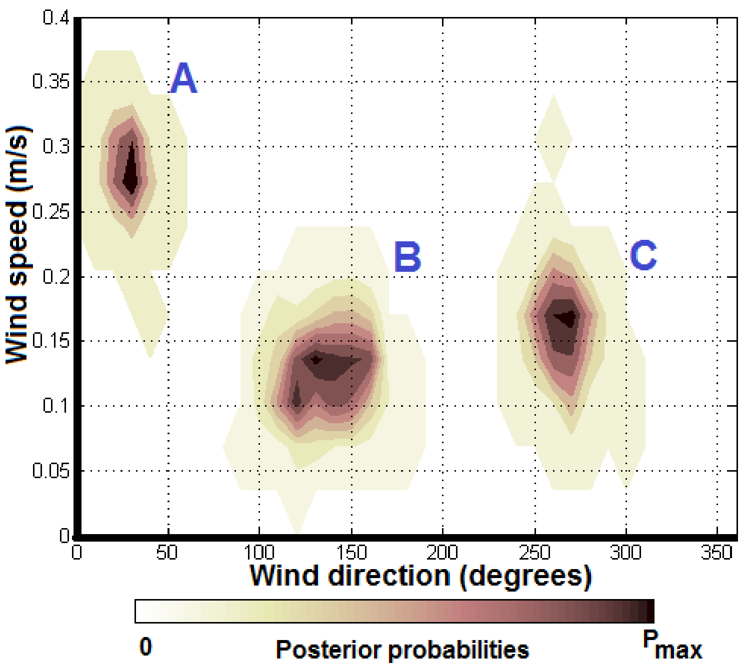
- (3) Estimate joint distribution of speed and direction at each measurement location





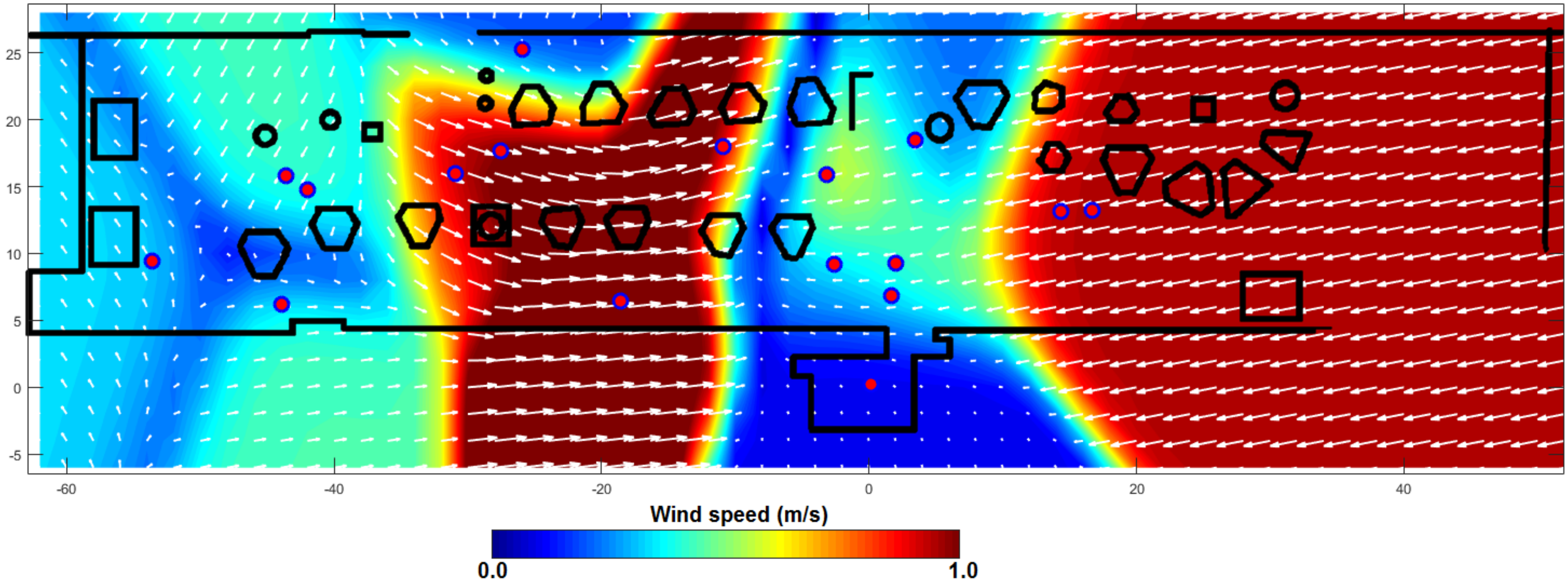
- **KKS Project RAISE, Robot Airflow Mapping Process**
  - (4) Extrapolation over probability distributions to estimate the joint distributions at non visited locations





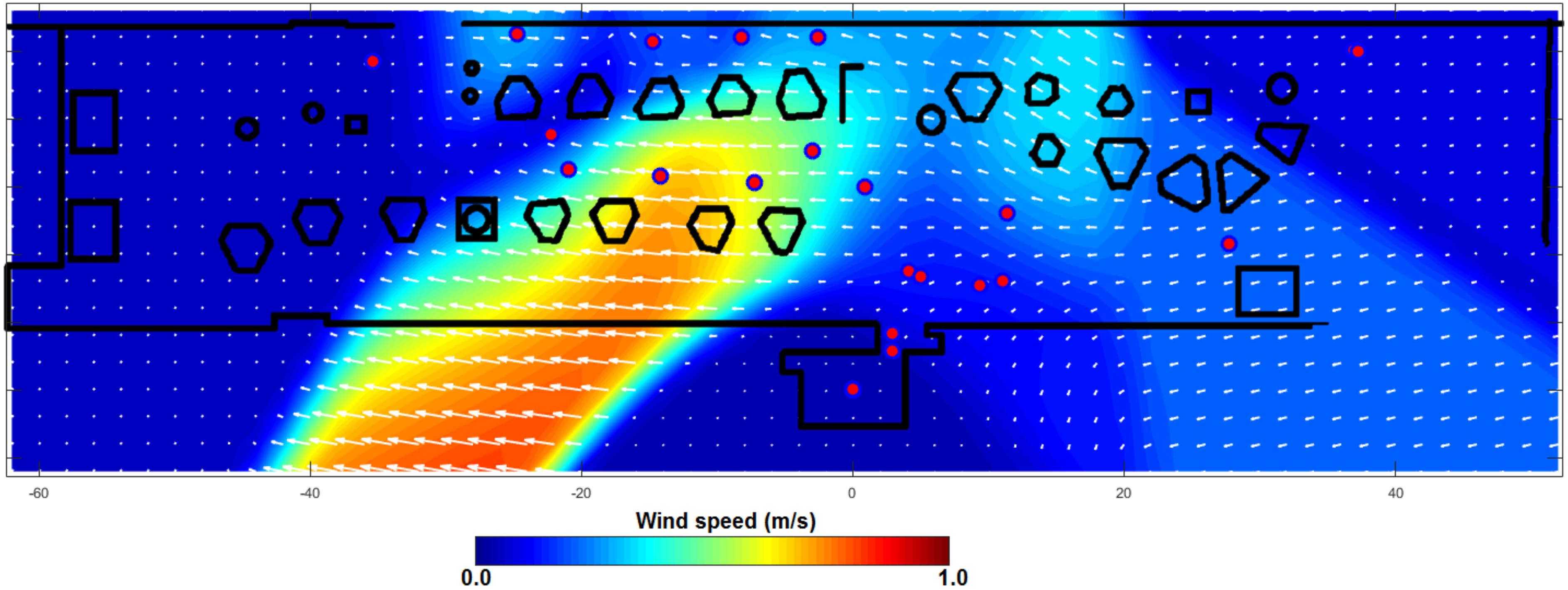
KKS Project RAISE, Robot Airflow Mapping Process

- Airflow mapping at Foundry B
  - Apr 15, 2015, 10:00am

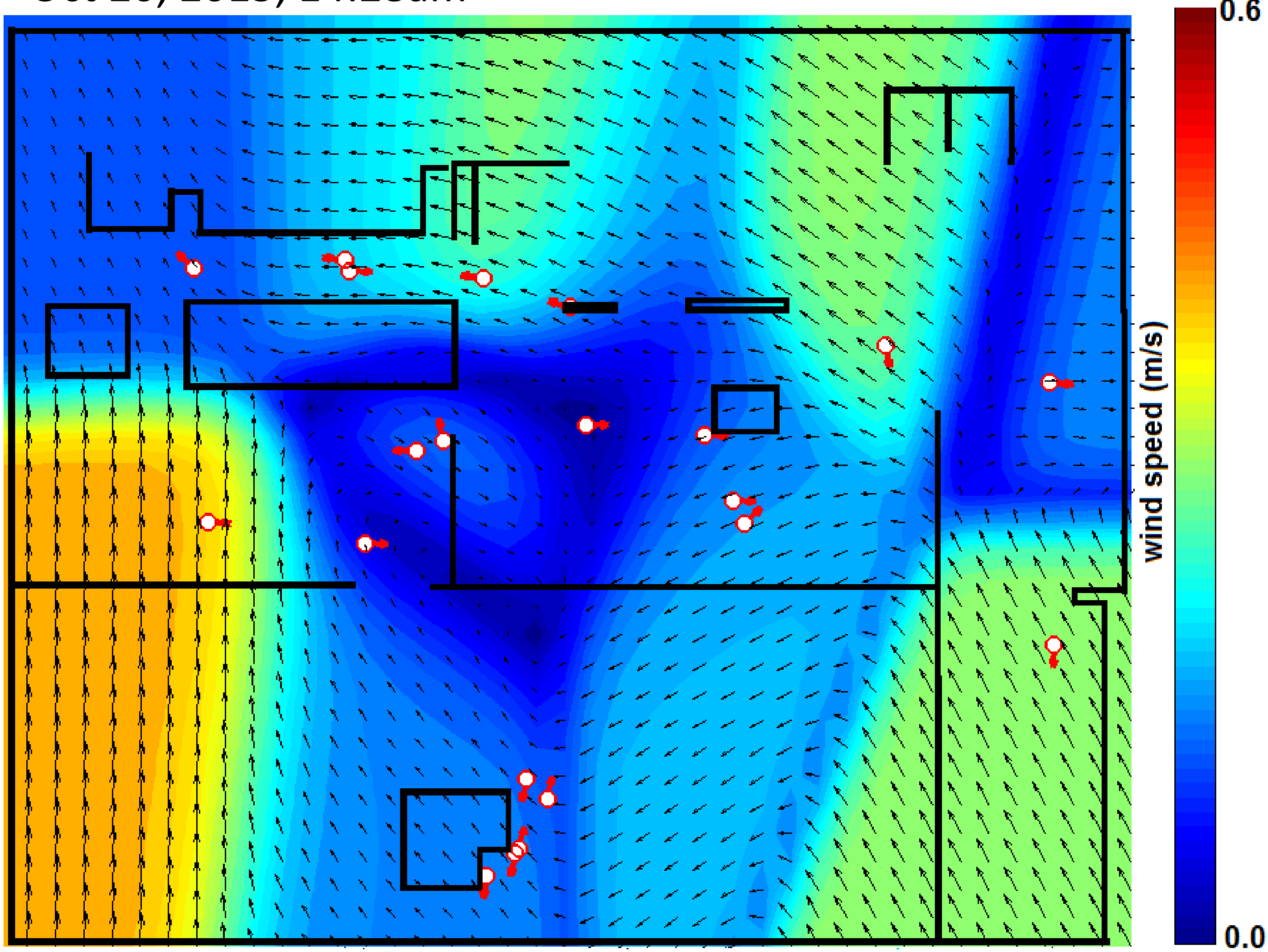


KKS Project RAISE, Robot Airflow Mapping Process

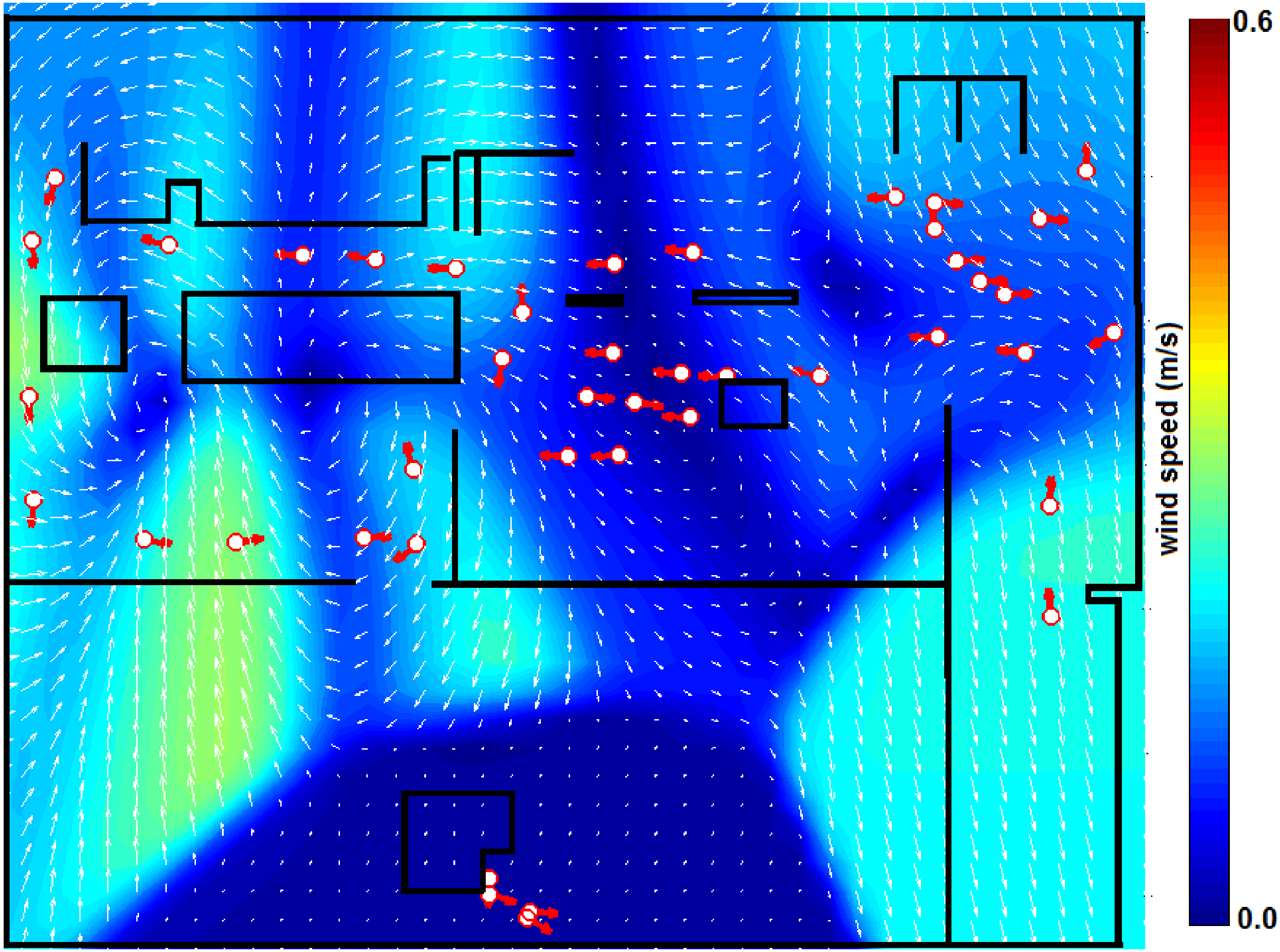
- Airflow mapping at Foundry B
  - Apr 17, 2015, 9:30am



- **KKS Project RAISE, Robot Airflow Mapping Process**
  - Airflow mapping at Foundry A
    - Oct 20, 2015, 14:28am



- **KKS Project RAISE, Robot Airflow Mapping Process**
  - Airflow mapping at Foundry A
    - Feb 2, 2016, 7:30am



Conclusions

- Airflow maps can be produced from mobile robot data
- Short term maps/snapshots
- Airflow maps from two foundries were computed
- Mapping carried out during different days
- Well defined airstreams are usually predicted

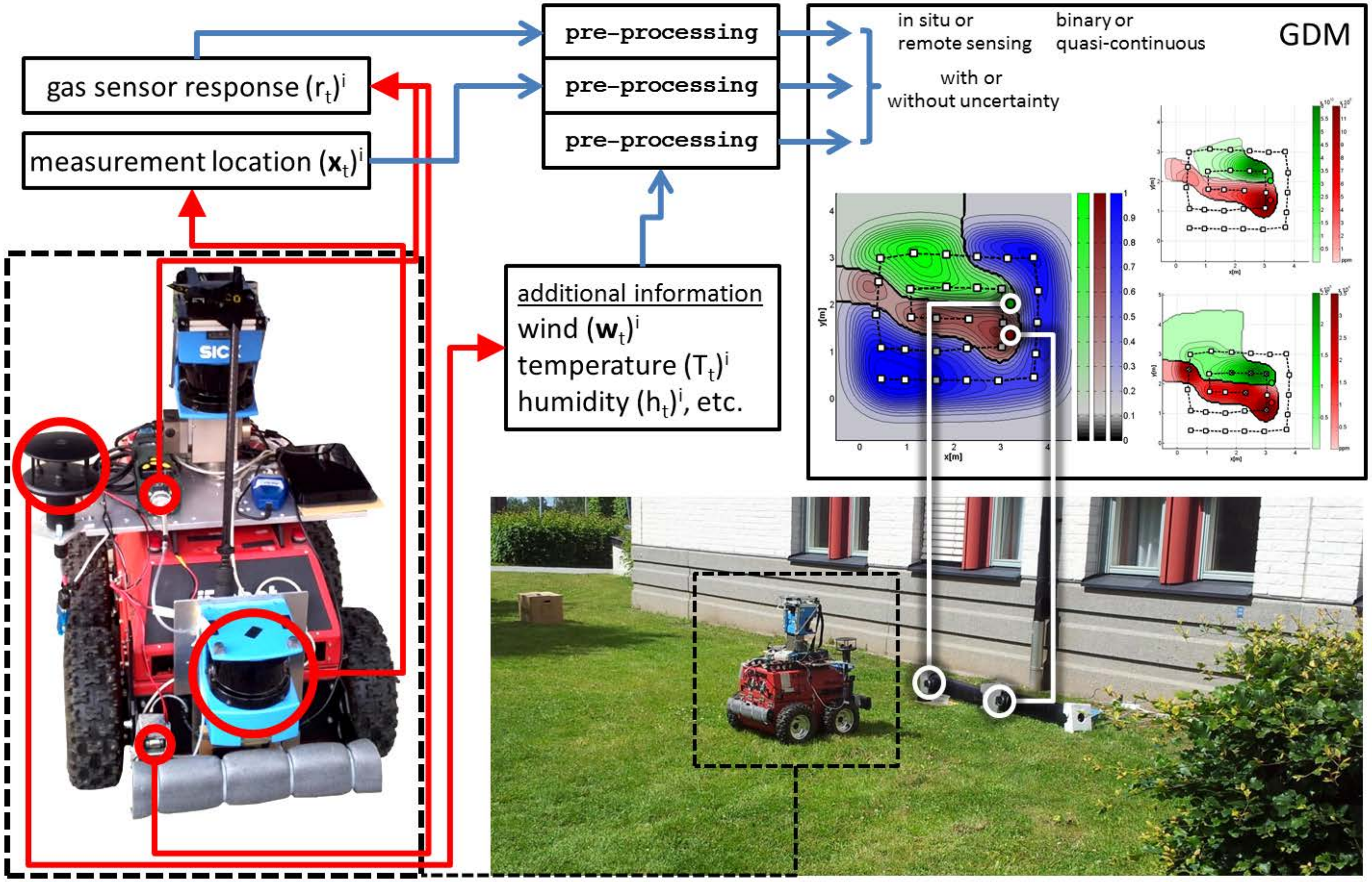
Open questions

- Lack of ground truth
- Numerical evaluation of the model
- Long term airflow models
- Obstacle dependent airflow maps
- Inclusion of partial analytic modelling (CFD)

Summary

- **A Brief Introduction to Mobile Robot Olfaction**
  - Basic Idea

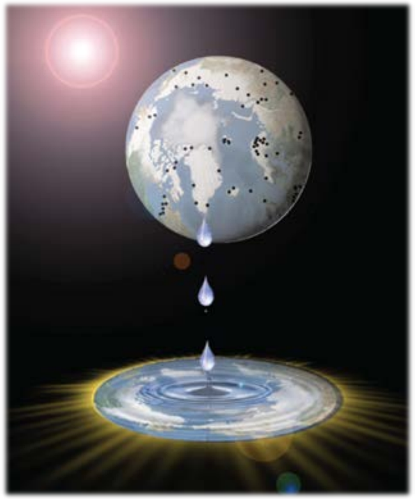
- **A Brief Introduction to Mobile Robot Olfaction**
  - o Basic Idea
  - o Subtasks / Gas Distribution Modelling

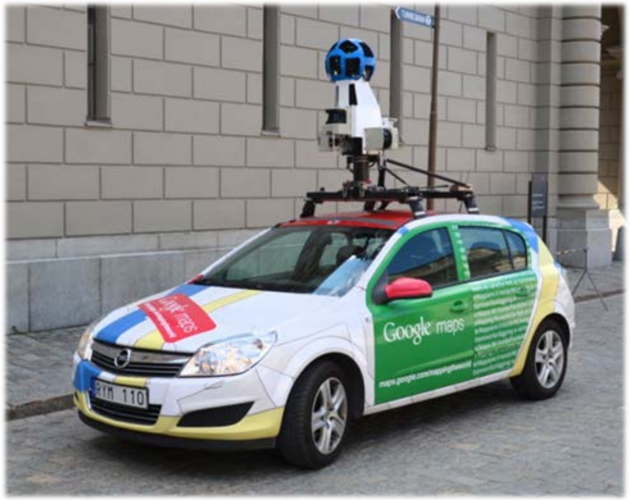


- **A Brief Introduction to Mobile Robot Olfaction**
  - Basic Idea
  - Subtasks / Gas Distribution Modelling
  - Advantages of Mobile Robot Environmental Monitoring

- Higher spatial resolution
- Fewer sensors needed
- Mobility
- Adaptability
- Accurate Positioning
- Rapid deployment
- Can be exposed to dangerous environments
- Can carry out more than one task simultaneously

- A Brief Introduction to Mobile Robot Olfaction
- **Why Do We Need Gas-Sensitive Robots?**
  - Dedicated Gas-Sensitive Robots
    - Search and Rescue
      (gas source localization, e.g. detecting leaks)
    - Surveillance, Environmental Monitoring
    - Scientific missions (climate research)





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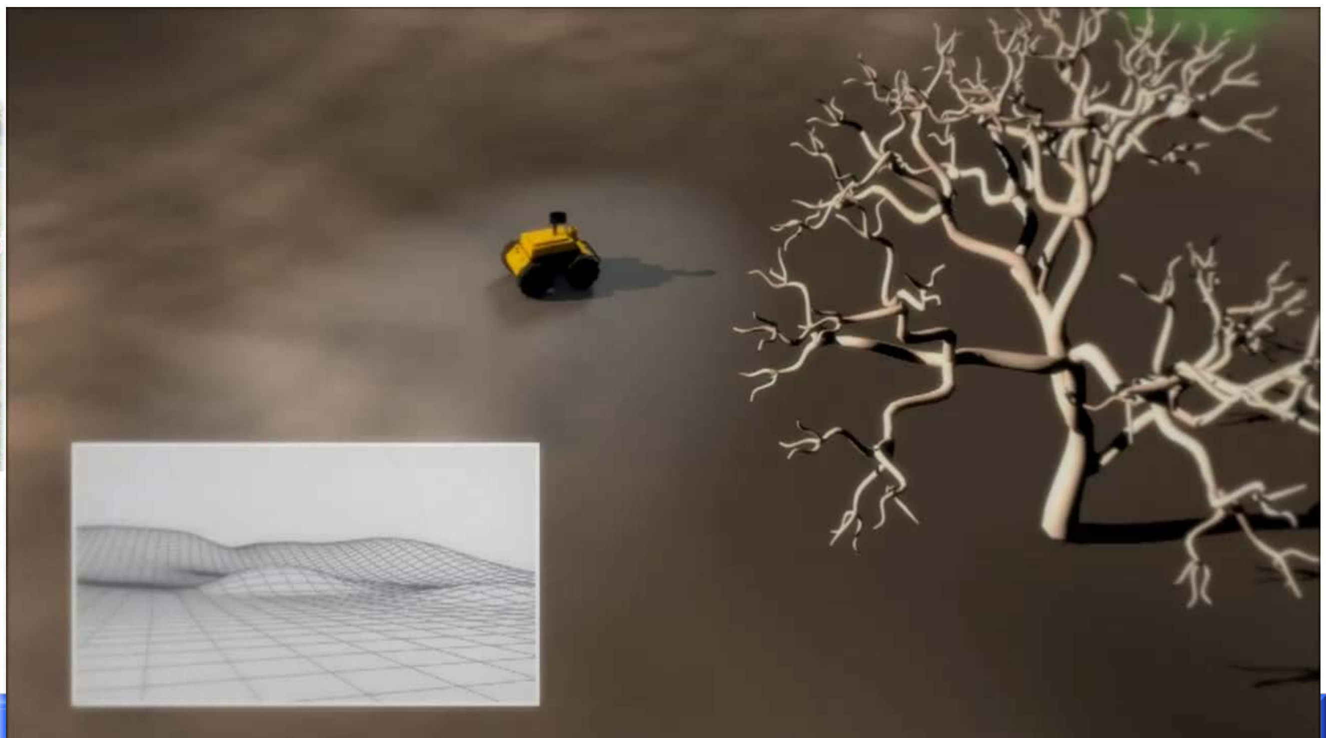

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  - Gas Sensing as Addition to Available Robots (DustBot)
    - Detect leaking gas pipes
    - Detect fire at its initial stage (CO)
    - Monitor pollutants in the environment

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    - Gas Sensing as Addition to Available Robots (DustBot)
        - Detect leaking gas pipes
        - Detect fire at its initial stage (CO)
        - Monitor pollutants in the environment
    - Robots as support and supplement for sensor networks
        - E.g.: KKS project RAISE

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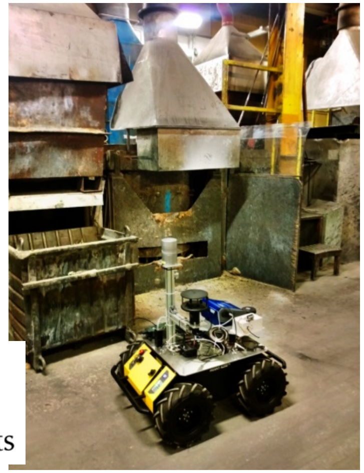
RAISE
Robotic System for Air Quality Assessment in Industrial Environments



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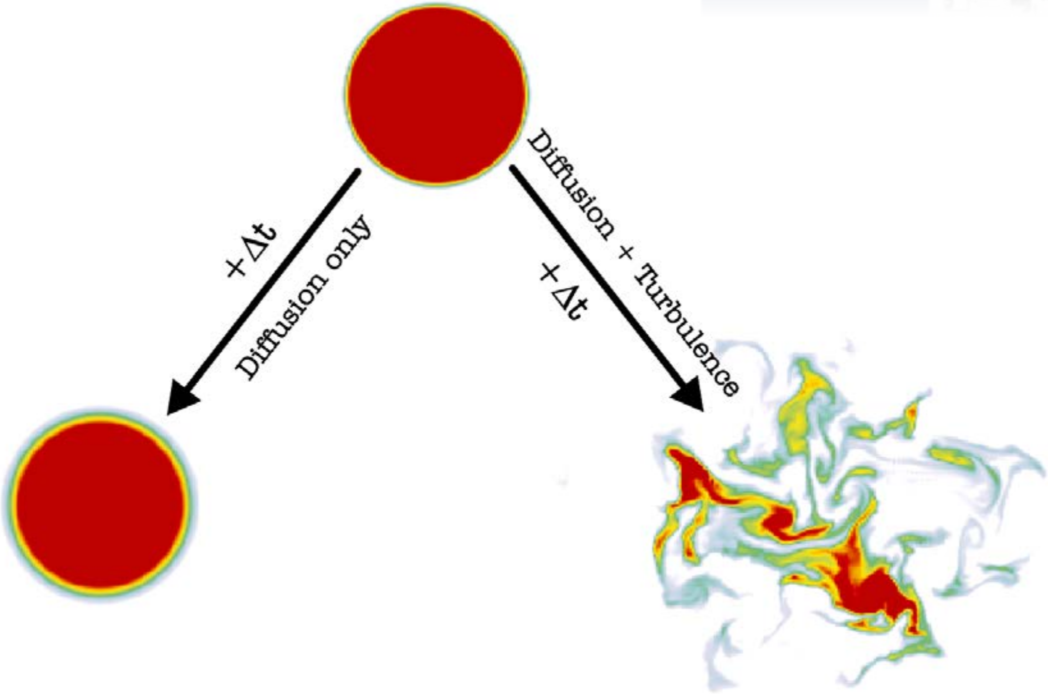
- Why Do We Need Gas-Sensitive Robots?
- **Mobile Robot Olfaction is Hard!**
  - Gas dispersal in natural environments (turbulence)



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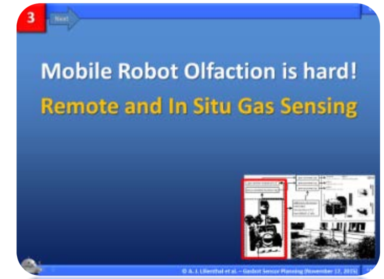
- Why Do We Need Gas-Sensitive Robots?
- **Mobile Robot Olfaction is Hard!**
  - Gas dispersal in natural environments (turbulence)
  - General sensing challenges
    - Weight/power restrictions, dynamic environment
  - In Situ Sensing
    - General challenges, incl. point character of measurements
    - MOX sensors, incl. problem that steady state is never reached
  - Remote sensing
    - Incl. integral measurements



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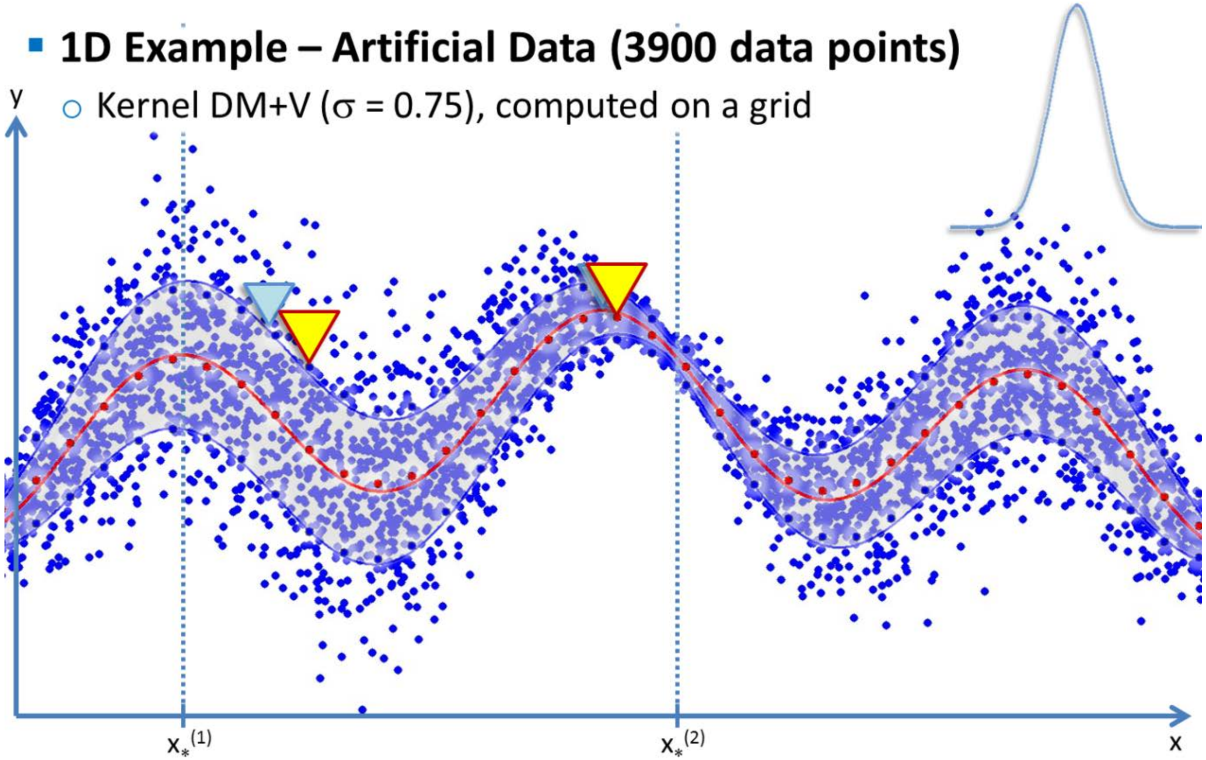
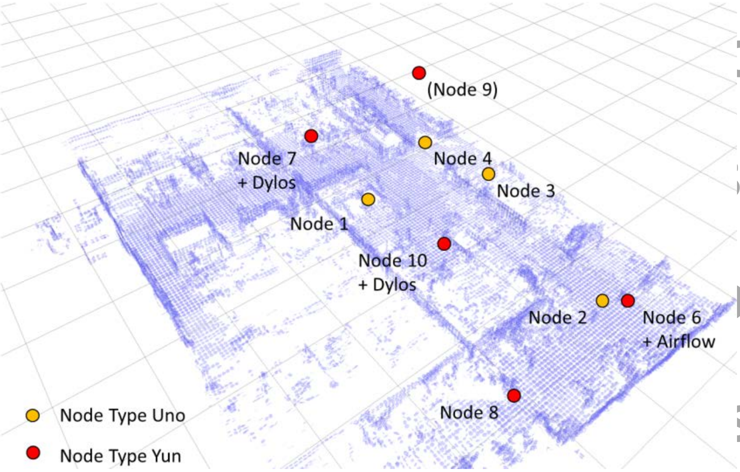
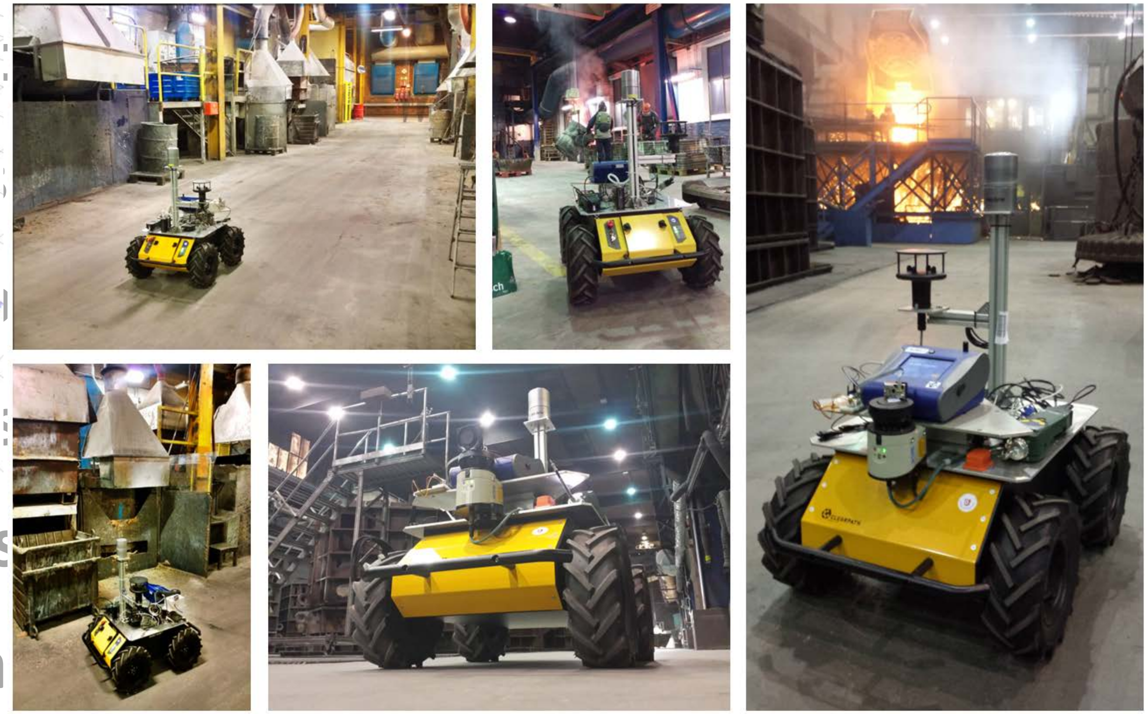
- **GDM with In Situ Sensors, Quasi-Continuous Input**







- GDM with In Situ Sens
- GDM with Remote Ga
- **Robot Supported Air Quality Monitoring Sensor Networks**

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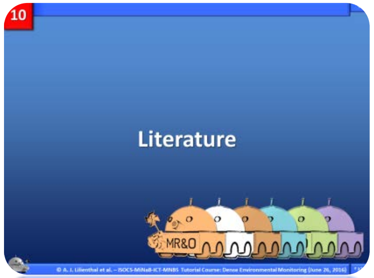
- GDM with In Situ Sensors, Quasi-Continuous Input
- GDM with In Situ Sensors, Discrete Input
- GDM with Remote Gas Sensors, RA-GT
- Robot Supported Air C itoring Sensor Networks
- **Summary**
- **Ongoing and Future Work**
- **References**



Mobile Robot Olfaction

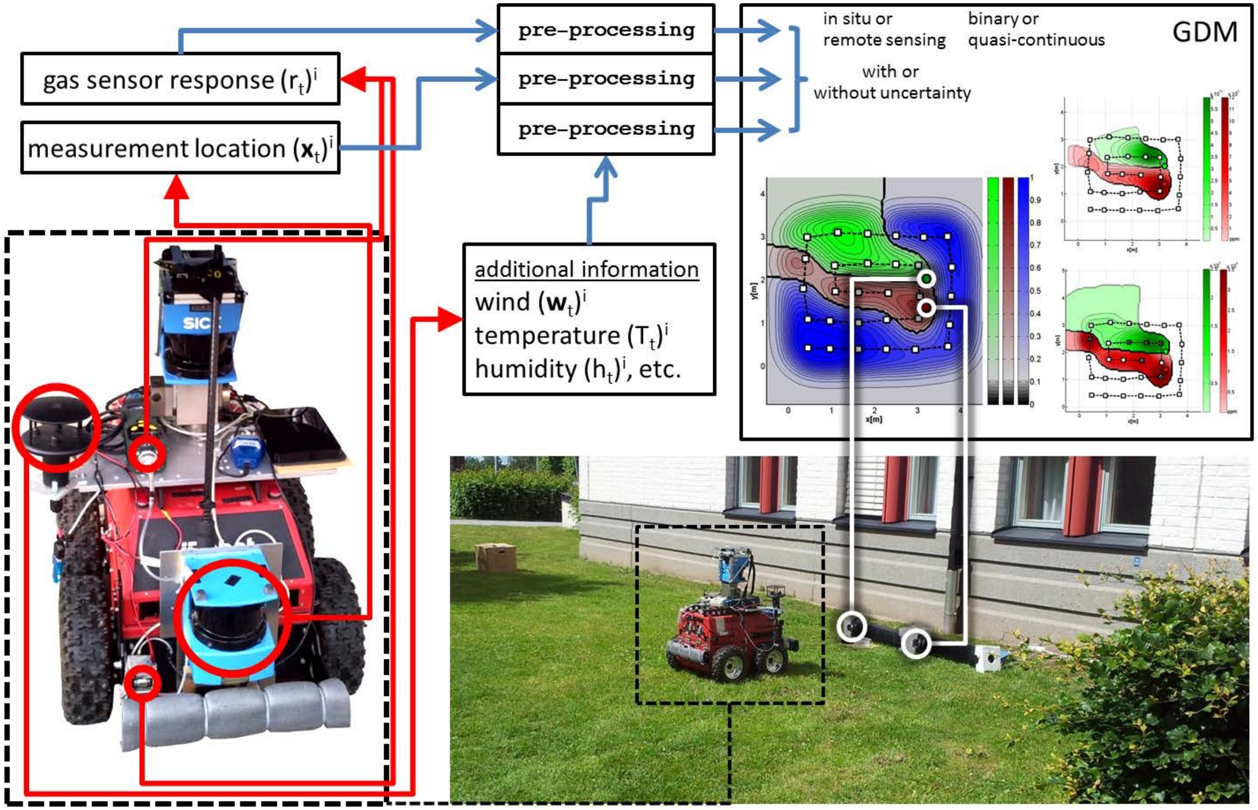
Ongoing and Future Work

- **Mobile Robot Olfaction, Current State**
  - Started in the 1990's
  - Today specific real-world applications are in reach, however ...

Mobile Robot Olfaction, Current State

- Started in the 1990's
- Today specific real-world applications are in reach
- Basic problems remain unaddressed
- Proposed solutions are heuristic and mono-disciplinary

- **Breakthroughs Needed!**
  - Evaluation of MRO systems
    - Lack of ground truth in validation runs
    - Repeatability
    - Time consuming experiments



- **Breakthroughs Needed!**
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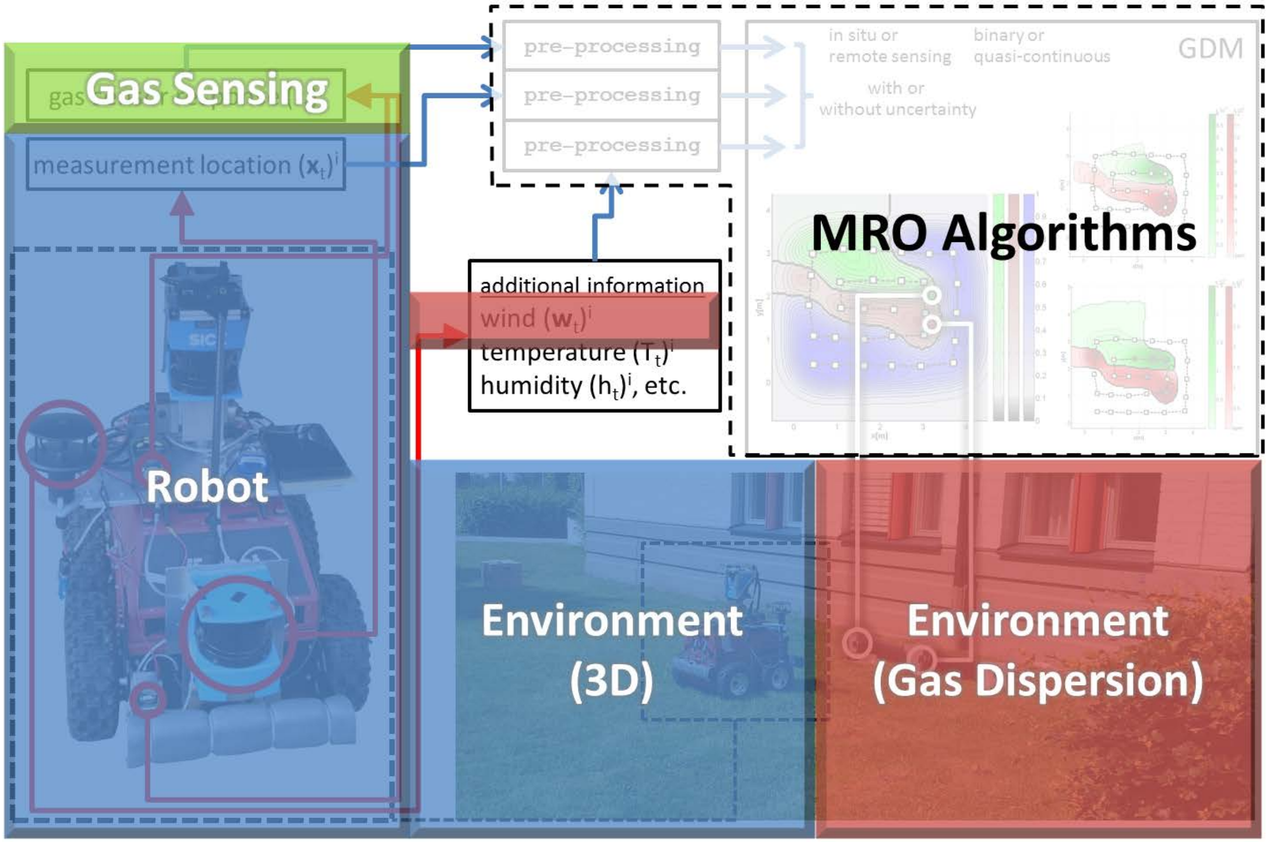
    - Time consuming experiments
    - → Develop simulation and experimentation means to evaluate MRO systems better



[Hernandez Bennetts et al., RSS 2015]

- **Breakthroughs Needed!**
  - Evaluation of MRO systems
    - Full ground truth evaluation of MRO systems is currently not possible
    - MRO systems often poorly understood / cannot be convincingly validated
    - → Develop simulation and experimentation means to evaluate MRO systems

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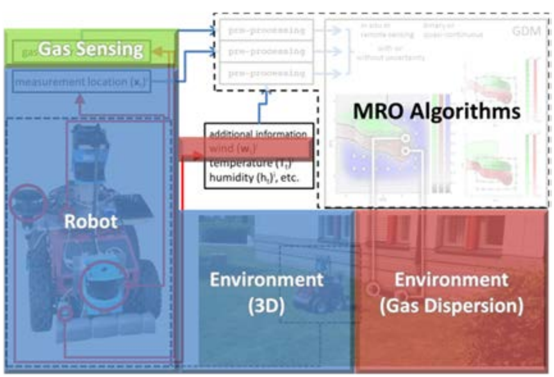
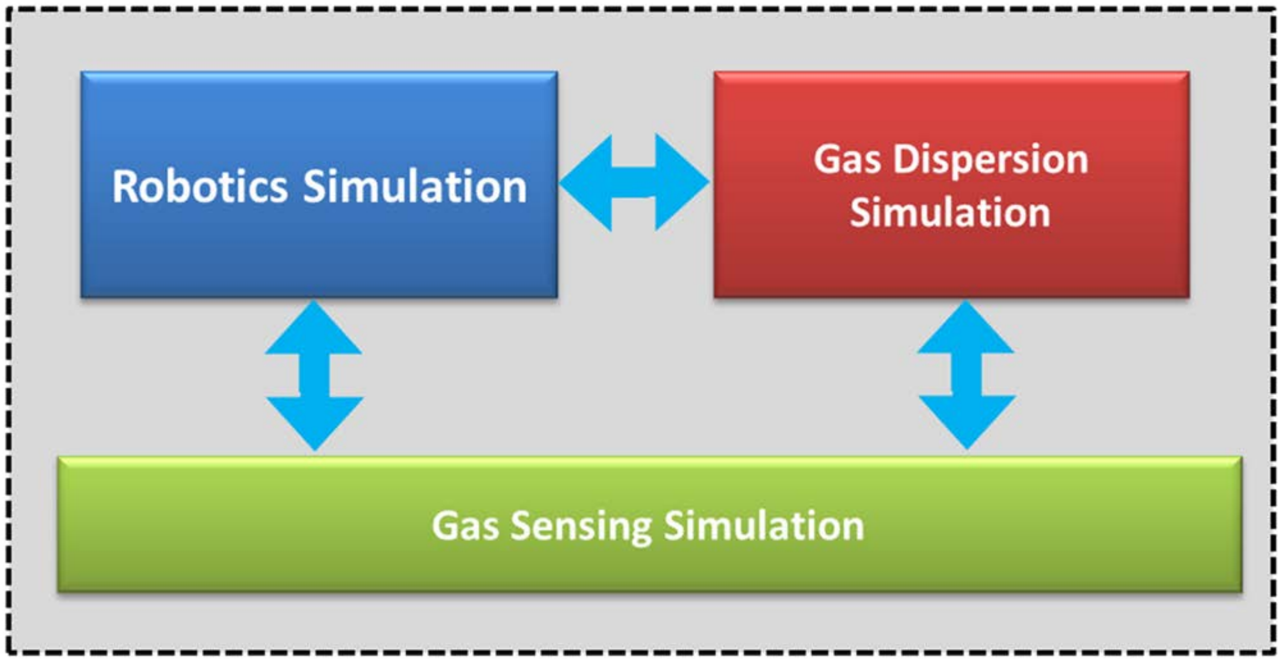
College of Engineering



ROS



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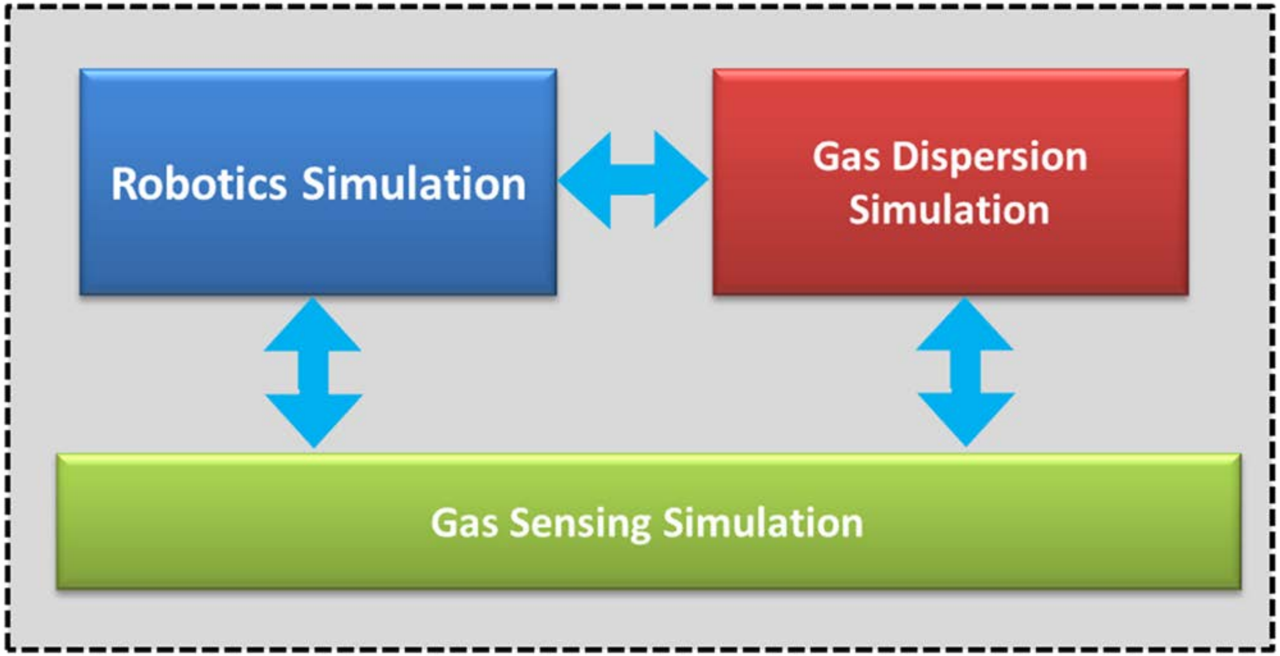
      https://bitbucket.org/vhbennetts/gas_dispersion_simulator

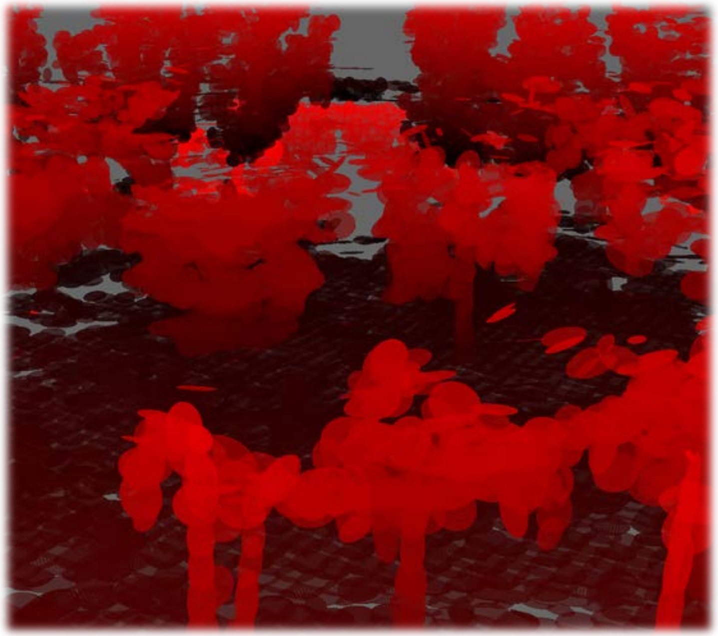
[Hernandez Bennetts et al., RSS 2015]

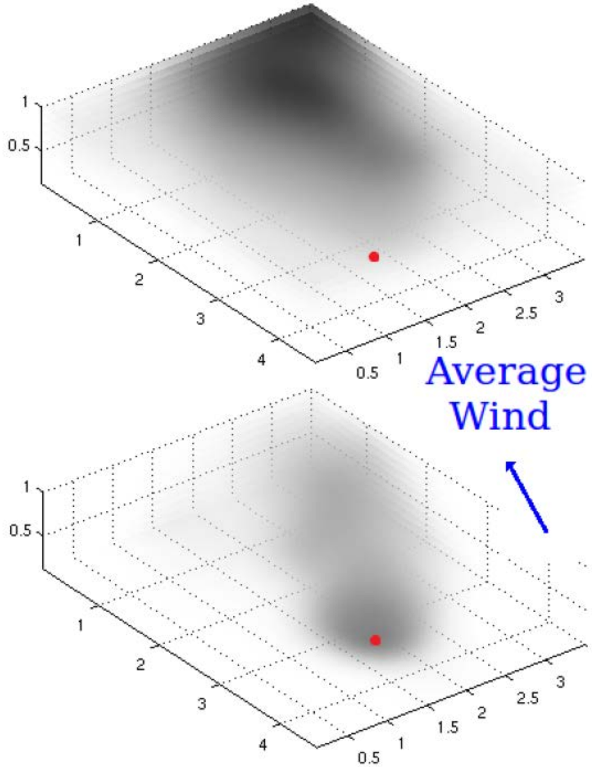
ROS



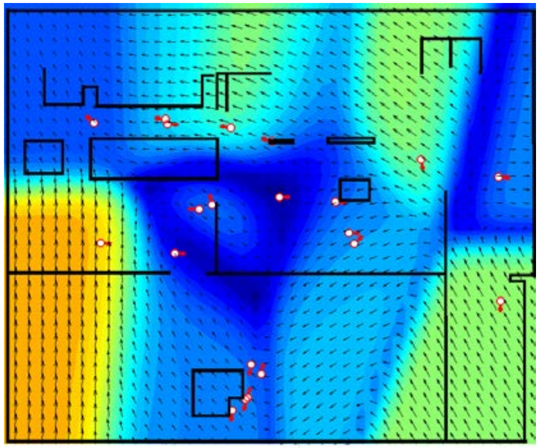
[Reggente/Lilienthal, ISOEN 2009]

- **Breakthroughs Needed!**
  - Means to evaluate MRO systems
  - 3D perception / 3D gas sensing
    - Almost all work in MRO models gas in 2D
    - Gas dispersal is a 3D process determined by the spatial 3D structure
    - → Develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches





- **Breakthroughs Needed!**
  - Means to evaluate MRO systems
  - 3D perception / 3D gas sensing
    - » → Develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches
  - Integration of wind distribution models
    - » Only instantaneous wind measurements have been used in MRO so far, directly associated to gas sensor readings or in a sequential decision chain often under unrealistic assumptions
    - » → Gas perception must build and integrate wind distribution models



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  - Rich 3D perception
    - → Models of other relevant properties such as temperature, humidity or reflectivity have to be included into the 3D model used for gas perception

[Neumann et al., RAM 2012]

- **Breakthroughs Needed!**
  - Means to evaluat
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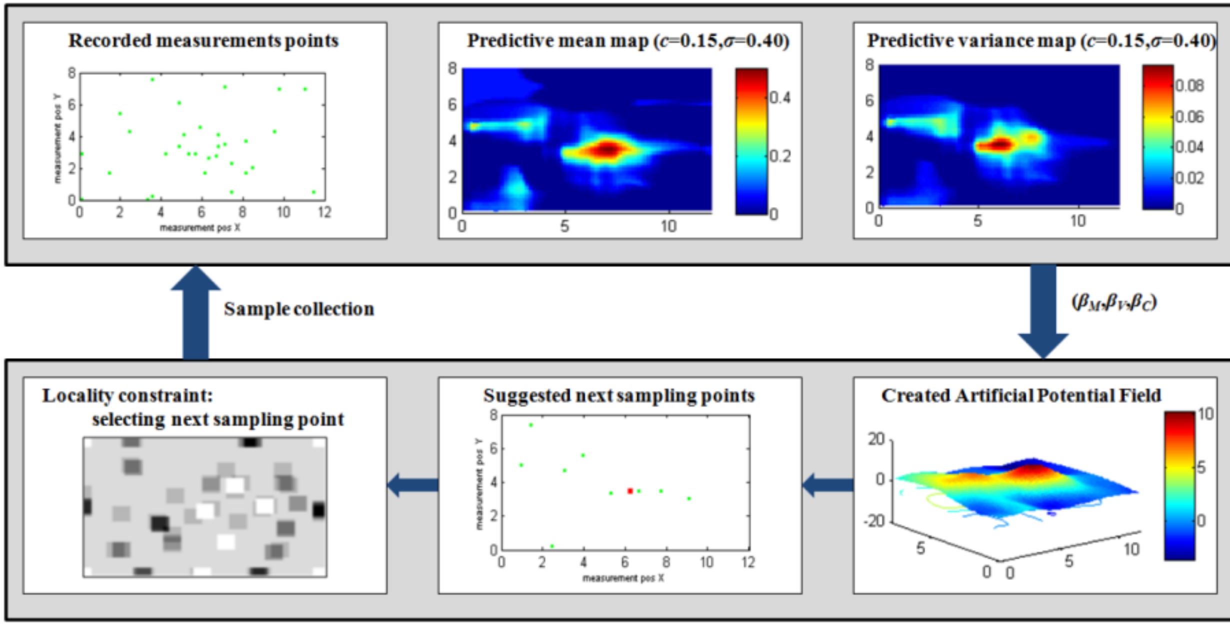

  - Sensor planning
    - » Under-sampling is generally prevalent in environmental monitoring
    - » → Sensor planning: adaptive sampling with high density where required
      - … for in-situ gas sensors

- **Breakthroughs Needed!**
  - Means to evaluate MRO systems
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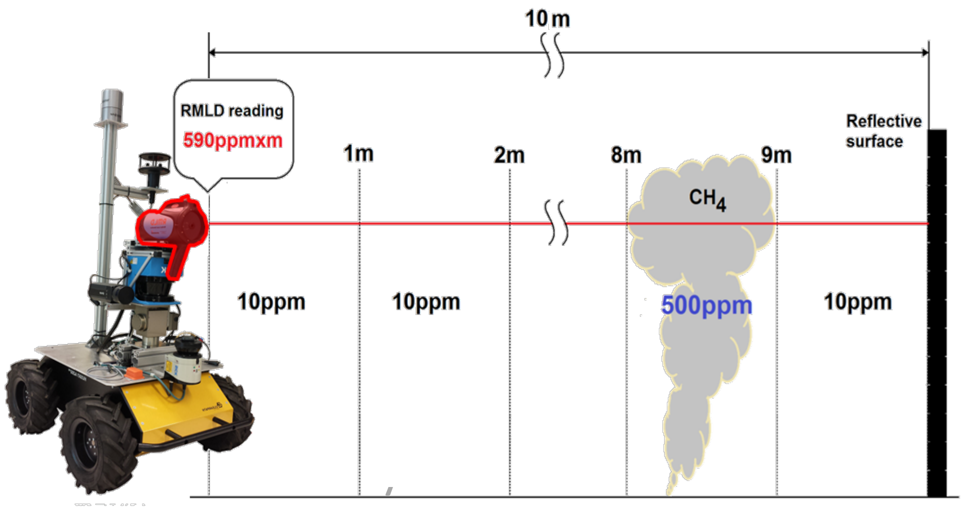

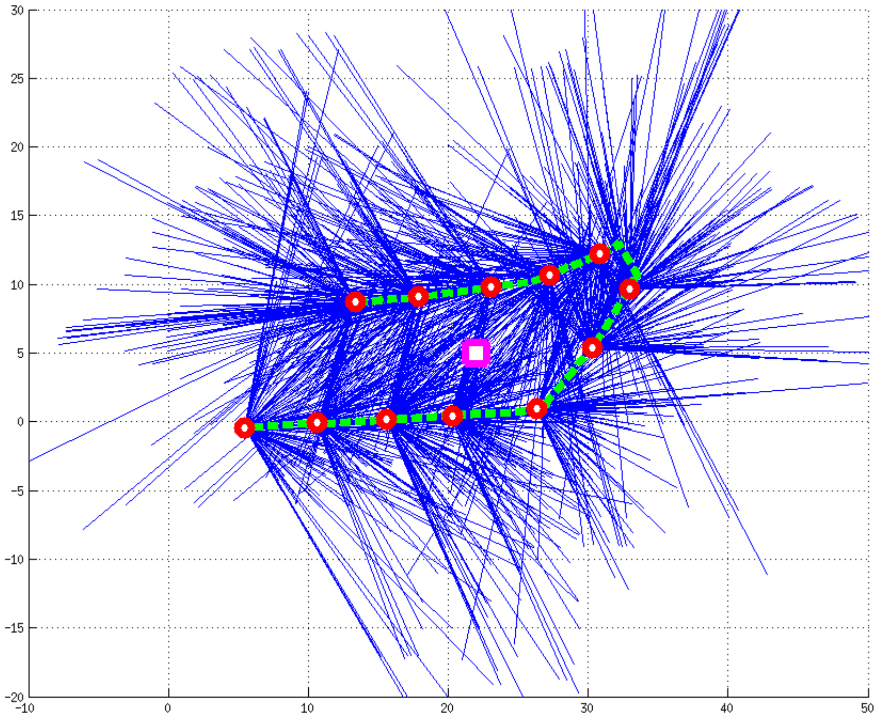

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      - … and remote gas sensors

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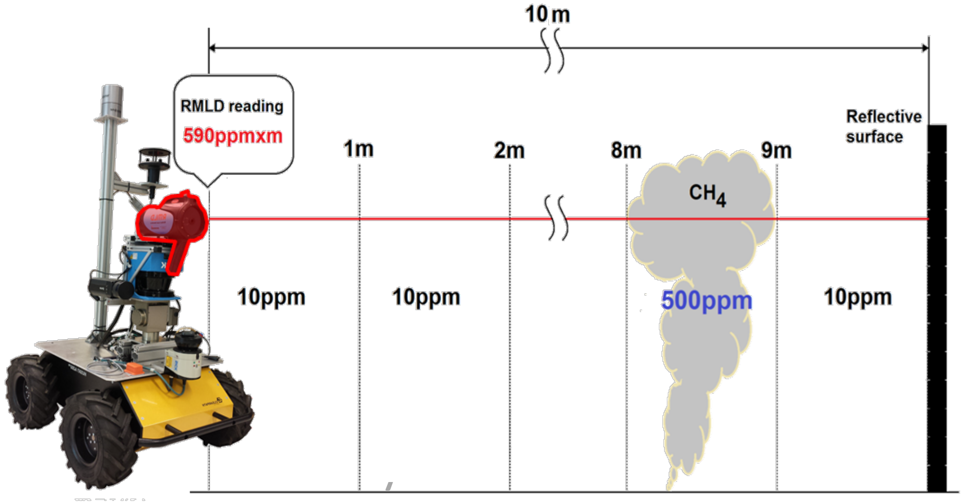

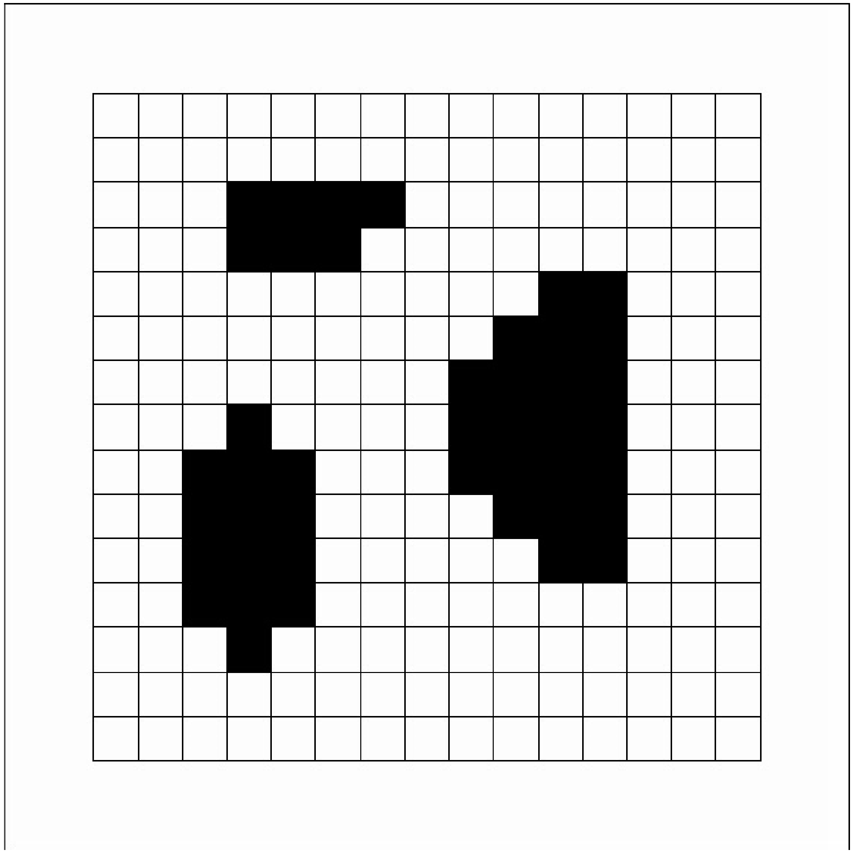

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[Arain et al., ICRA 2015]
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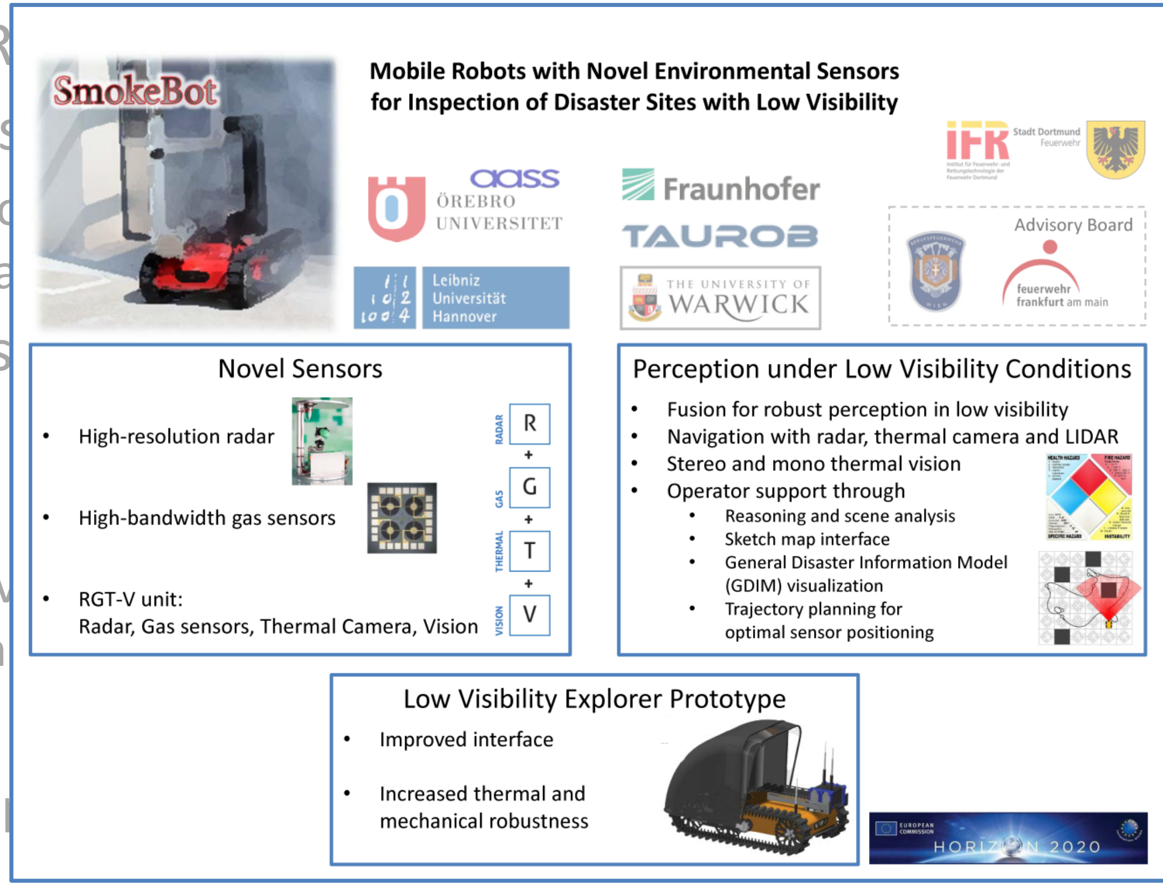
    - … and remote gas sensors
    - … with complex additional constraints

Breakthroughs Needed!



- Sensors for Gasbots
  - Gas sensors used in MRO so far were developed for laboratory use
  - → Develop new sensors tailored for open sampling systems on a robot

- **Breakthroughs Needed!**

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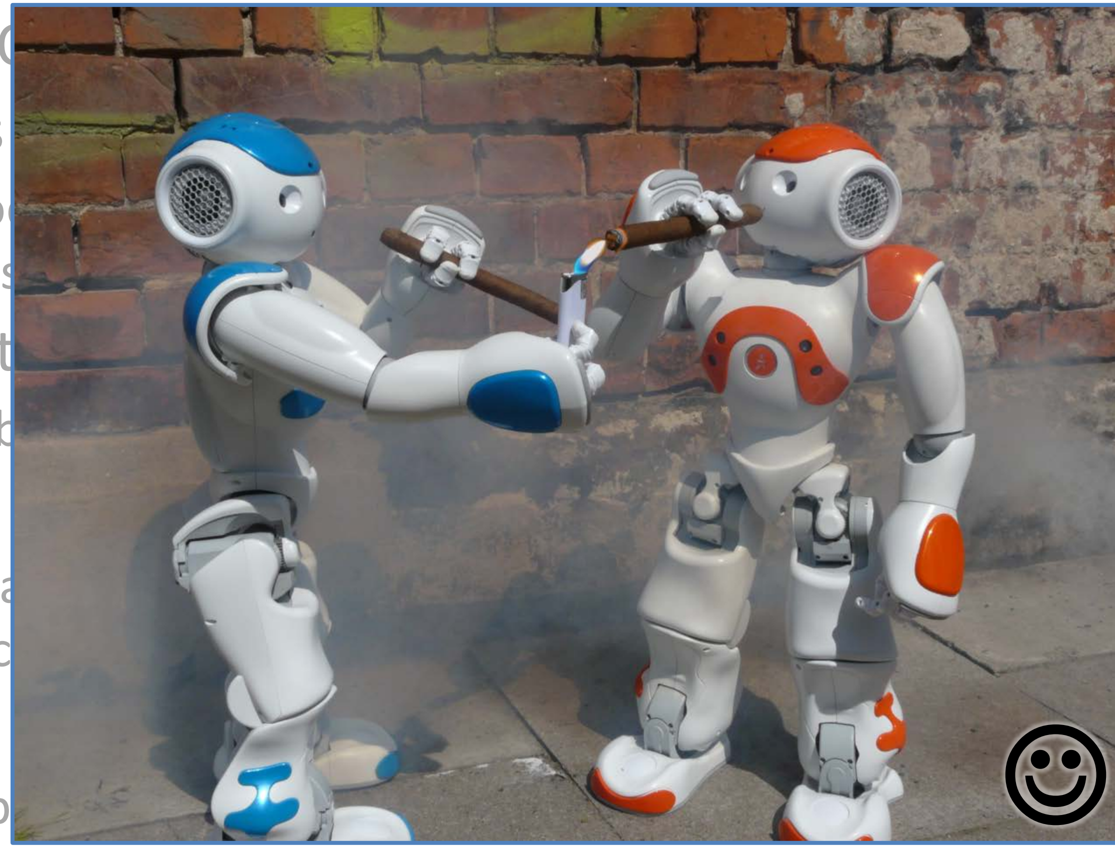

  - Sensors for Gasbots (SmokeBot)
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Ongoing and Future Work

- **Breakthroughs Needed!**
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  - Flying Gasbots
    - Superior mobility makes multicopters promising for MRO

Ongoing and Future Work

- **Breakthroughs Needed!**
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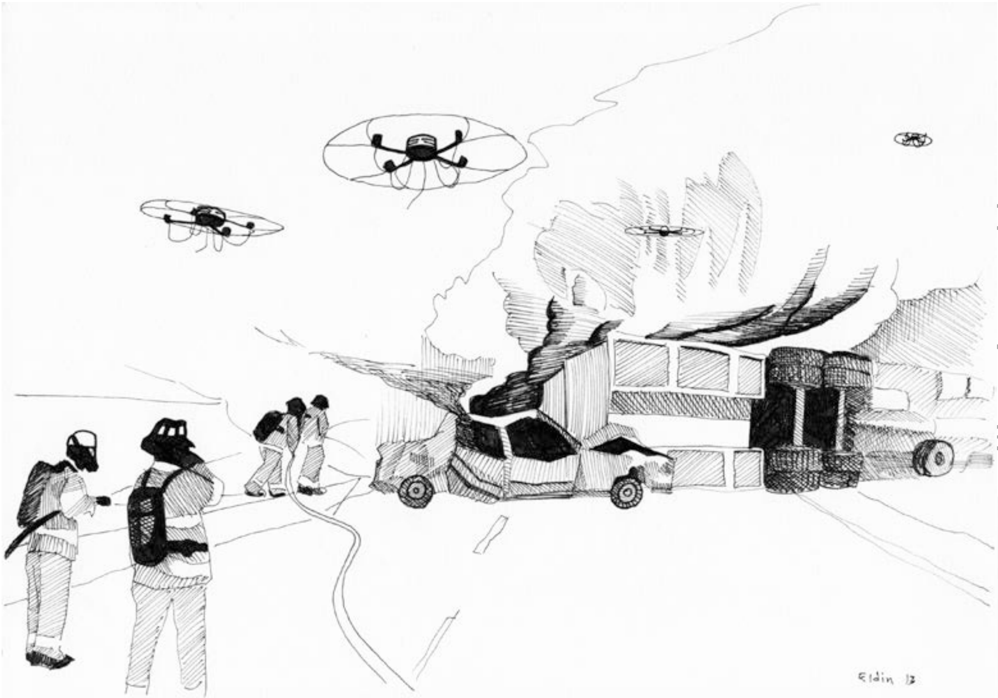
    - Superior mobility makes multicopters promising for MRO
    - → Study interaction with gas distributions to minimize disturbance

- **Breakthroughs Needed!**



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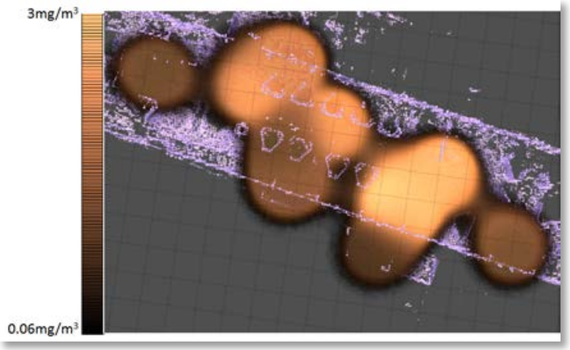
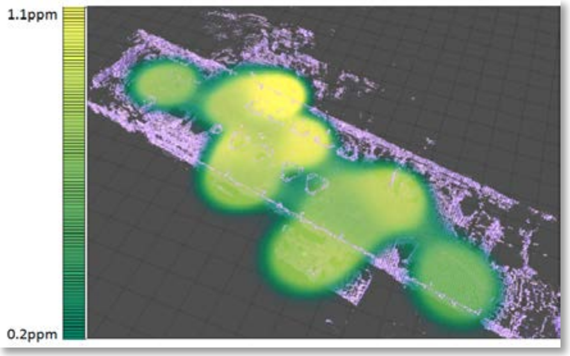
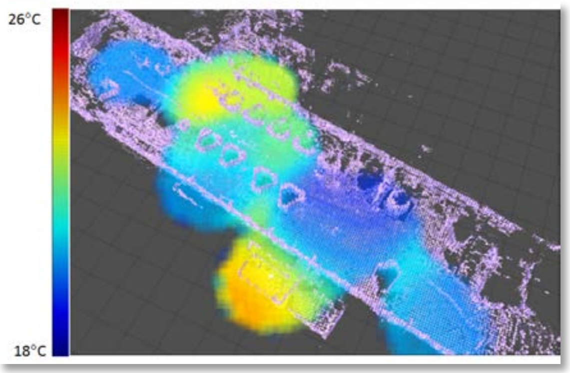
- Sensors for Gasbots
  - → Develop new sensors tailored
- Flying Gasbots
  - → Study interaction with gas dist
- New Applications

Breakthroughs Needed!

- KKS Project RAISE (Industrial Air Quality Assessment, 2014 – 2017)
  - Robotic System for Air Quality Assessment in Industrial Environments
  - E.g: dust, gas and temperature maps







- New Applications

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Acknowledgement

Joint work with:

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  - EU H2020 Project SmokeBot (LowVis Explorer, 2015 – 2018)
  - KKS Project RAISE (Industrial Air Quality Assessment, 2014 – 2017)
  - Robotdalen Project Gasbot (Biogas monitoring, 2011 – 2013)
  - EU FP7 Project Diadem (Environmental Decision-Making, 2008 – 2011)
  - EU FP6 Project DustBot (Robots for Urban Hygiene, 2006 – 2010)

THANKS!!!!

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Dense Environmental Monitoring w
Stationary and Mobile Sensing Nodes

Tutorial Course: Distributed Chemical Sensing
For Remote Environmental Monitoring

8 Summary

9 Mobile Robot Olfaction
Ongoing and Future Work

10 Literature

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Remote and In Situ Gas Sensing

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5 GDM with In Situ Sensors
Discrete Input (Binary)

5 Motivation
The DIADEM Project
Diadem

6 GDM with Remote Gas Sensors
Robot Assisted Gas Tomography

7 Robot Supported Air Quality
Monitoring Sensor Networks
From Foundries to Urban Sensing

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Thanks for your attention!

Dense Environmental Monitoring with Stationary and Mobile Sensing Nodes

Tutorial Course: Distributed Chemical Sensing For Remote Environmental Monitoring

Achim J. Lilienthal

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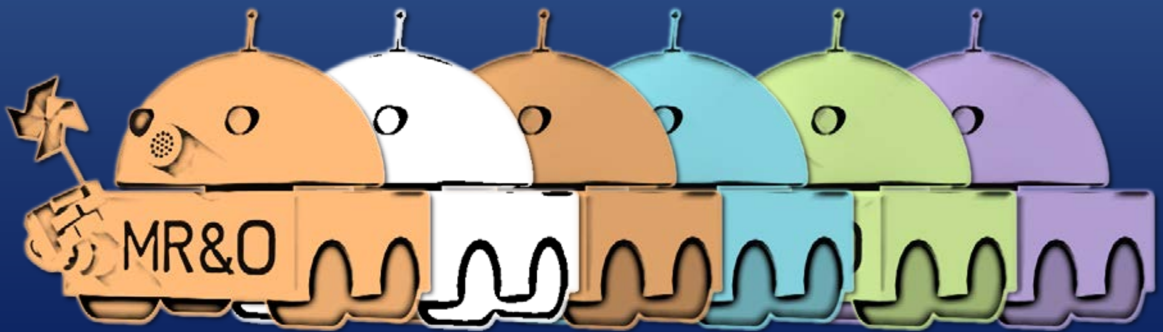
Literature



Gas-sensitive Mobile Robots

- V. Hernandez Bennetts, A. J. Lilienthal, P. P. Neumann and M. Trincavelli.
  Mobile Robots for Localizing Gas Emission Sources on Landfill Sites: Is Bio-Inspiration the Way to go?
  Frontiers in Neuroengineering, 4, 2012, pp. 1 - 12.

- G. Kowadlo and R. A. Russell.
  Robot Odor Localization: A Taxonomy and Survey.
  IJRR, 27, 2008, pp. 869 - 894.

- A. J. Lilienthal, A. Loutfi and T. Duckett.
  Airborne Chemical Sensing with Mobile Robots.
  Sensors, 6, 2006, pp. 1616 - 1678.

- Michael Wandel, Achim Lilienthal, Tom Duckett, Udo Weimar and Andreas Zell.
  Gas Distribution in Unventilated Indoor Environments Inspected by a Mobile Robot.
  Proc. IEEE Int. Conf. on Advanced Robotics (ICAR), 2003, pp. 507-512.

Turbulence

- P. J. W. Roberts, D. R. Webster.
  Turbulent Diffusion.
  Environmental Fluid Mechanics - Theories and Application. ASCE Press, Reston, Virginia, 2002.

- W. D. Smyth, J. N. Moum.
  3D Turbulence.
  Encyclopedia of Ocean Sciences. Academic Press, 2001.

Gas-sensitive Mobile Robots, Applications (1)

- V. Hernandez Bennetts, E. Schaffernicht, A. J. Lilienthal, H. Fan, T. P. Kucner, L. Andersson, A. Johansson.
  Towards Occupational Health Improvement in Foundries Through Dense Dust and Pollution Monitoring Using a Complementary Approach with Mobile and Stationary Sensing Nodes.
  Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2016, under review.

- V. Hernandez Bennetts, A. J. Lilienthal, A. Abdul Khaliq, V. Pomareda Sesé and M. Trincavelli.
  Towards Leak Inspection and Gas Distribution Mapping Using Mobile Robots and TDLAS Sensing Technologies.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2013, pp. 2327 - 2332.

Gas-sensitive Mobile Robots, Applications (2)

- S. Asadi, C. Badica, T. Comes, C. Conrado, V. Evers, F. Groen, S. Illie, J. Steen Jensen, A. J. Lilienthal, B. Milan, K. Nieuwenhuis, S. Pashami, G. Pavlin, J. Pehrsson, R. Pinchuk, M. Scafes, L. Schou-Jensen, F. Schultmann and N. Wijngaards.
  ICT Solutions Supporting Collaborative Information Acquisition, Situation Assessment And Decision Making In Contemporary Environmental Management Problems: The Diadem Approach.
  Int. Conf. on Innovations in Sharing Environmental Observation and Information (EnviroInfo), 2011.

- M. Reggente, A. Mondini, G. Ferri, B. Mazzolai, A. Manzi, M. Gabelletti, P. Dario and A. J. Lilienthal.
  The DustBot System: Using Mobile Robots to Monitor Pollution in Pedestrian Area.
  Chemical Engineering Transactions, 23, 2010, pp. 273-278.

Gas-sensitive Mobile Robots, Applications (3)

- M. Trincavelli, M. Reggente, S. Coradeschi, A. Loutfi, H. Ishida and A. J. Lilienthal.
  Towards Environmental Monitoring with Mobile Robots.
  Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2008, pp. 2210 - 2215.

Gas-Sensitive UAVs

- P. P. Neumann, S. Asadi, V. Hernandez Bennetts, A. J. Lilienthal, and M. Bartholmai.
  Monitoring of CCS Areas using Micro Unmanned Aerial Vehicles (MUAVs).
  Energy Procedia, 37, 2013, 4182-4190.

- P. P. Neumann, V. Hernandez Bennetts, A. J. Lilienthal, M. Bartholmai and J. H. Schiller.
  Gas Source Localization with a Micro-Drone using Bio-Inspired and Particle Filter-based Algorithms.
  Advanced Robotics (AR), Special Issue on Aerial Robots, 27:9, 2013, 725-738.

- P. P. Neumann, S. Asadi, A. J. Lilienthal, M. Bartholmai and J. H. Schiller.
  Autonomous Gas-Sensitive Microdrone: Wind Vector Estimation and Gas Distribution Mapping.
  IEEE Robotics & Automation Magazine (RAM), 19:1, 2012, pp. 50 - 61.

Change Detection

- S. Pashami, A. J. Lilienthal and M. Trincavelli.
  Detecting Changes of a Distant Gas Source with an Array of MOX Gas Sensors.
  Sensors, 14(9), 2014, pp. 17331 - 17352.

- S. Pashami, A. J. Lilienthal, E. Schaffernicht and M. Trincavelli.
  TREFEX: Trend Estimation and Change Detection in the Response of MOX Gas Sensors.
  Sensors, Special Issue "Gas Sensors - 2013", 13(6), June 4, 2013, pp. 7323 - 7344.

Gas Distribution Mapping, In Situ Gas Sensors (1)

- V. Hernandez Bennetts, E. Schaffernicht, V. Pomareda, A. J. Lilienthal, S. Marco and M. Trincavelli.
  Combining Non Selective Gas Sensors on a Mobile Robot for Identification and Mapping of Multiple Chemical Compounds.
  Sensors, 14(9), 2014, pp. 17331 - 17352.

- V. Hernandez Bennetts, E. Schaffernicht, A. J. Lilienthal and M. Trincavelli.
  A Novel Approach for Gas Discrimination in Natural Environments with Open Sampling Systems.
  Proc. IEEE Sensors Conference, 2014, pp. 2046 - 2049.

- E. Schaffernicht, M. Trincavelli and A. J. Lilienthal.
  Bayesian Spatial Event Distribution Grid Maps for Modeling the Spatial Distribution of Gas Detection Events.
  Sensor Letters, 12 (6-7), 2014, pp. 1142 - 1146.

Gas Distribution Mapping, In Situ Gas Sensors (2)

- A. J. Lilienthal, M. Trincavelli and E. Schaffernicht.
  It's always smelly around here! Modeling the Spatial Distribution of Gas Detection Events with BASED Grid Maps.
  Int. Symposium on Olfaction and Electronic Nose (ISOEN), 2013.

- V. Hernandez Bennetts, A. J. Lilienthal and M. Trincavelli.
  Creating True Gas Concentration Maps in Presence of Multiple Heterogeneous Gas Sources.
  Proc. IEEE Sensors Conference, 2012, pp. 554 - 557.

- M. Reggente and A. J. Lilienthal.
  Three-Dimensional Statistical Gas Distribution Mapping in an Uncontrolled Indoor Environment.
  AIP Conf. Proc. Vol. 1137: Olfaction and Electronic Nose – Proc. 13th Int. Symposium on Olfaction and Electronic Nose (ISOEN), 2009, pp. 109-112.

Gas Distribution Mapping, In Situ Gas Sensors (3)

- A. J. Lilienthal, S. Asadi and M. Reggente.
  Estimating Predictive Variance for Statistical Gas Distribution Modelling.
  AIP Conf. Proc. Vol. 1137: Olfaction and Electronic Nose – Proc. 13th Int. Symposium on Olfaction and Electronic Nose (ISOEN), 2009, pp. 65-68.

- A. J. Lilienthal, M. Reggente, M. Trincavelli, J. Luis Blanco, and J. Gonzalez.
  A Statistical Approach to Gas Distribution Modelling with Mobile Robots – The Kernel DM+V Algorithm.
  Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2009, pp. 570-576.

- A. J. Lilienthal, A. Loutfi, J. L. Blanco, C. Galindo and J. Gonzalez.
  A Rao-Blackwellisation Approach to GDM-SLAM - Integrating SLAM and Gas Distribution Mapping.
  Proc. 3rd European Conf. on Mobile Robots (ECMR), 2007, pp. 126-131.

Gas Distribution Mapping, In Situ Gas Sensors (4)

- A. J. Lilienthal and T. Duckett.
  Building Gas Concentration Gridmaps with a Mobile Robot.
  Robotics and Autonomous Systems, 48:1, 1 December 2004, pp. 3-16.

- A. J. Lilienthal and T. Duckett.
  Creating Gas Concentration Gridmaps with a Mobile Robot.
  Proc. Int. Conf. Intelligent Robots and Systems (IROS), 2003, pp. 118-123.

- A. T. Hayes, A. Martinoli, R. M. Goodman.
  Distributed Odor Source Localization.
  IEEE Sensors, 2:3, 2002, pp. 260–273.

- A. T. Hayes, A. Martinoli, R. M. Goodman.
  Swarm Robotic Odor Localization.
  Proc. Int. Conf. Intelligent Robots and Systems (IROS), 2001, pp. 1073-1078.

Gas Distribution Mapping, Remote Gas Sensors

- V. M. Hernandez Bennetts, E. Schaffernicht, T. Stoyanov, A. J. Lilienthal and M. Trincavelli.
  Robot Assisted Gas Tomography - Localizing Methane Leaks in Outdoor Environments.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA) 2014, pp. 6362 - 6367.

- V. M. Hernandez Bennetts, A. J. Lilienthal, A. Abdul Khaliq, V. Pomareda Sesé and M. Trincavelli.
  Towards Leak Inspection and Gas Distribution Mapping Using Mobile Robots and TDLAS Sensing Technologies.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2013, pp. 2327 - 2332.

- M. Trincavelli, V. Hernandez Bennetts and A. J. Lilienthal.
  A Least Squares Approach for Learning Gas Distribution Maps from a Set of Integral Gas Concentration Measurements Obtained with a TDLAS Sensor.
  Proc. IEEE Sensors Conference, 2012, pp. 550 - 553.

Gas Source Declaration

- Achim Lilienthal, Holger Ulmer, Holger Fröhlich, Andreas Stützle, Felix Werner and Andreas Zell.
  Gas Source Declaration with a Mobile Robot.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2004, pp. 1430-1435.

- Achim Lilienthal, Holger Ulmer, Holger Fröhlich, Andreas Stützle, Felix Werner and Andreas Zell.
  Learning to Detect Proximity to a Gas Source with a Mobile Robot.
  Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2004, pp. 1444-1449.

Gas Source Localization (1)

- T. A. Foster-Wittig, E. D. Thoma, and J. D. Albertson.
  Estimation of Point Source Fugitive Emission Rates from a Single Sensor Time Series: a Conditionally-Sampled Gaussian Plume Reconstruction.
  Atmospheric Environment, 2015.

- T. Lochmatter.
  Bio-Inspired and Probabilistic Algorithms for Distributed Odor Source Localization using Mobile Robots.
  Ph.D. Thesis, EPFL Lausanne, 2009.

- A. Lilienthal, F. Streichert and A. Zell.
  Model-based Shape Analysis of Gas Concentration Gridmaps for Improved Gas Source Localisation.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2005, pp. 3575-3580.

- Achim Lilienthal and Tom Duckett.
  Experimental Analysis of Gas-Sensitive Braitenberg Vehicles.
  Advanced Robotics, Volume 18, Number 8, 1 December 2004, pp. 817-834.

Gas Source Localization (2)

- Achim Lilienthal and Tom Duckett.
  Experimental Analysis of Smelling Braitenberg Vehicles.
  Proc. IEEE Int. Conf. on Advanced Robotics (ICAR), 2003, pp. 375-380.

- Achim Lilienthal, Andreas Zell, Michael Wandel and Udo Weimar.
  Sensing Odour Sources in Indoor Environments Without a Constant Airflow by a Mobile Robot.
  Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2001, pp. 4005-4010.

- R. Rozas, J. Morales and D. Vega.
  Artificial Smell Detection for Robotic Navigation.
  Proc. Int. Conf. on Advanced Robotics (ICAR), 1991, pp. 1730 - 1733.

Gas Discrimination with MOX-OSS

- Marco Trincavelli.
  Gas Discrimination for Mobile Robots.
  Künstliche Intelligenz, 25: 4, 2011, pp. 351-354.

- M. Trincavelli, S. Coradeschi and A. Loutfi.
  Odour classification system for continuous monitoring applications.
  Sensors and Actuators B: Chemicals, 139: 2, 2009, pp. 265 – 273.

- M. Trincavelli, S. Coradeschi and A. Loutfi.
  Classification of Odours for Mobile Robots Using an Ensemble of Linear Classifiers.
  Proc. of Int. Symp. on Olfaction and Electronic Nose (ISOEN), 2009, 475 - 478.

Gas Dispersal Simulation (1)

- V. Hernandez Bennetts, A. J. Lilienthal, E. Schaffernicht, S. Ferrari, and J. Albertson.
  Integrated Simulation of Gas Dispersion and Mobile Sensing Systems.
  RSS Workshop on Realistic, Rapid and Repeatable Robot Simulation (R4SIM), July 16, 2015.

- J. G. Monroy, J.-L. Blanco, and J. González-Jiménez.
  An Open Source Framework for Simulating Mobile Robotics Olfaction.
  15th Int. Symposium on Olfaction and Electronic Nose (ISOEN), 2013.

- S. Pashami, S. Asadi, and A. J. Lilienthal.
  Integration of OpenFOAM Flow Simulation and Filament-Based Gas Propagation Models for Gas Dispersion Simulation.
  Proc. Open Source CFD International Conference, 2010.

Gas Dispersal Simulation (2)

- G. Cabrita, J. Sousa, and L. Marques.
  Plumesim – Player/Stage Plume Simulator.
  ICRA 2010 Workshop on Networked and Mobile Robot Olfaction.

- J. A. Farrell, J. Murlis, X. Long, and W. Li.
  Filament-Based Atmospheric Dispersion Model to Achieve Short Time-Scale Structure of Odour Plumes.
  Environmental Fluid mechanics, vol. 2, no. 1, pp. 143–169, 2002.

- **Sensor Planning (1)**
  - M. Asif Arain, E. Schaffernicht, V. M. Hernandez Bennetts, A. J. Lilienthal.
    The Right Direction to Smell: Efficient Sensor Planning Strategies for Robot Assisted Gas Tomography.
    Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2016.
  - M. Asif Arain, M. Trincavelli, M. Cirillo, E. Schaffernicht, and A. J. Lilienthal.
    Global Coverage Measurement Planning Strategies for Mobile Robots equipped with a Remote Gas Sensor.
    Sensors, 15:3, 2015, pp. 6845 – 6871.
  - M. Asif Arain, M. Cirillo, V. M. Hernandez Bennetts, E. Schaffernicht, M. Trincavelli, A. J. Lilienthal.
    Efficient Measurement Planning for Remote Gas Sensing with Mobile Robots.
    Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), 2015, pp. 3428 - 3434.

Sensor Planning (2)

- C. Cai and S. Ferrari.
  Information-Driven Sensor Path Planning by Approximate Cell Decomposition.
  IEEE Transactions on Systems, Man, and Cybernetics - Part B, vol. 39, no. 2, 2009.

- C. Cai and S. Ferrari.
  Comparison of Information-Theoretic Objective Functions for Decision Support in Sensor Systems.
  Proc. American Control Conference, New York, NY, 2007, pp. 63–133.

- **Gas Quantification with MOX-OSS**
  - J. González Monroy, A. J. Lilienthal, J. Luis Blanco, J. González Jimenez and M. Trincavelli.
    Probabilistic Gas Quantification with MOX Sensors in Open Sampling Systems - A Gaussian Process Approach.
    Sensors and Actuators B: Chemicals, 188, 2013, 298-312.

3D World Modelling, NDT (1)

- J. P. Saarinen, H. Andreasson, T. Stoyanov and A. J. Lilienthal.
  3D Normal Distributions Transform Occupancy Maps: An Efficient Representation for Mapping in Dynamic Environments.
  International Journal of Robotics Research (IJRR), 2013, pp. 1627 - 1644.

- T. Stoyanov, J. Saarinen, H. Andreasson and A. J. Lilienthal.
  Normal Distributions Transform Occupancy Map Fusion: Simultaneous Mapping and Tracking in Large Scale Dynamic Environments.
  Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2013, pp. 4702 – 4708.

- T. Stoyanov, M. Magnusson and A. J. Lilienthal.
  Comparative Evaluation of the Consistency of Three-Dimensional Spatial Representations used in Autonomous Robot Navigation.
  Journal of Field Robotics (JFR), 30:2, 2013, pp. 216 - 236.

3D World Modelling, NDT (2)

- M. Magnusson, H. Andreasson, A. Nüchter and A. J. Lilienthal.
  Automatic Appearance-Based Loop Detection from 3D Laser Data Using the Normal Distributions Transform.
  Journal of Field Robotics, 26:11-12, 2009, 892-914.

- M. Magnusson, T. Duckett and A. J. Lilienthal.
  3D Scan Registration for Autonomous Mining Vehicles.
  Journal of Field Robotics, 24:10, 24 Oct 2007, pp. 803-827.

Thanks for your attention!

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