Mobile Robot Olfaction

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Now for something completely different ...
Mobile Robot Olfaction
Mobile Robot Olfaction

- Introduction
  - Gas-Sensitive Mobile Robots in the Real World

- Challenges for GDM
  - Gas Dispersion in Natural Environments

- Mobile Robot Olfaction
  - Key Contributions

- Gas Distribution Mapping
  - Selected Ongoing Work

- Mobile Robot Olfaction
  - Outlook

- References
Mobile Robot Olfaction
Mobile Robot Olfaction
Introduction

Gas-Sensitive Mobile Robots in the Real World
1. Basic Idea
   - to combine autonomous robots with ...
   - ... gas sensing technology ("electronic nose") and ...
   - ... eventually other relevant sensors
1. Basic Idea
   - autonomous robots + gas sensors + other relevant sensors

2. Applications: Gasbots for ...
   - environmental monitoring

[Hernandez Bennetts et al., ICRA 2013]
[Hernandez Bennets et al., FrontNeuroEng 2012]
[Reggente et al., ChemEngTrans 2010]
### Basic Idea
- autonomous robots + gas sensors + other relevant sensors

### Applications: Gasbots for ...
- environmental monitoring
- security applications (gas source localization, e.g. detecting leaks)
Introduction

Components of Mobile Robot Olfaction Systems
1. **Subtasks in Mobile Robot Olfaction**

   - gas detection (gas finding)
   - "odour" discrimination and concentration estimation
   - gas source tracking
   - gas source declaration
   - trail guidance
     - trail following
     - trail avoiding strategies
   - gas distribution mapping / gas distribution modelling
### Subtasks in Mobile Robot Olfaction

- gas detection (gas finding)
- "odour" discrimination and concentration estimation
- gas source tracking
- gas source declaration
- trail guidance
  - trail following
  - trail avoiding strategies
- gas distribution mapping / gas distribution modelling (GDM)
Components of MRO Systems – Example: GDM

- gas sensor response \((r_t)^i\)
- measurement location \((x_t)^i\)
- additional information
  - wind \((w_t)^i\)
  - temperature \((T_t)^i\)
  - humidity \((h_t)^i\), etc.

**Pre-processing**

- in situ or remote sensing
- binary or quasi-continuous
- with or without uncertainty

GDM
Challenges for GDM
Challenges for GDM

Gas Dispersal in Natural Environments
Gas Dispersal in Natural Environments

- Chaotic Gas Dispersal
  - diffusion

[Smyth and Moum 2001]
Gas Dispersal in Natural Environments

- Chaotic Gas Dispersal
  - diffusion

[Smyth and Moum 2001]
Chaotic Gas Dispersal

- diffusion
- advective transport
- turbulent transport

[Smyth and Moum, 2001]
2. Gas Dispersal in Natural Environments

- **Chaotic Gas Dispersal**
  - diffusion
  - advective transport
  - turbulent transport

[Smyth and Moum 2001]
2. Chaotic Gas Dispersal
   - diffusion
   - advective transport
   - turbulent transport

video courtesy of Hiroshi Ishida
Challenges for GDM

In Situ Gas Sensing with Mobile Robots
2. From "Electronic Nose" to "Mobile Nose"

- space, power, weight restrictions
- varying environmental conditions (temperature, humidity, ...)
- open sampling system
  - direct exposition of gas sensors to the environment
  - less controlled gas sampling
  - typically continuous sampling
Differences to Other Sensors in Mobile Robotics

- point measurement
  - sensitive sensor surface is typically small (often < 1cm²)
# Differences to Other Sensors in Mobile Robotics

- point measurement
- sensor dynamics
  - long response time, very long recovery time
2. Differences to Other Sensors in Mobile Robotics

- point measurement
- sensor dynamics
- calibration
  - complicated "sensor response ↔ concentration" relation
  - dependent on other variables (temperature, humidity, ...)
  - has to consider sensor dynamics
  - variation between individual sensors
  - long-term drift
Differences to Other Sensors in Mobile Robotics

- point measurement
- sensor dynamics
- calibration
- very dynamic reality
  - constantly changing chaotic concentration field
Differences to Other Sensors in Mobile Robotics

- sensor dynamics
  - long response time, very long recovery time
- very dynamic reality
  - constantly changing chaotic concentration field

[Trincavelli, KI 2011]
[Trincavelli et al., IROS 2008]

traditional three-phase sampling

steady state virtually never reached in Open Sampling Systems

continuous (open) sampling with a mobile robot
Challenges for GDM
Remote Gas Sensing with Mobile Robots
2. **Optical Sensor Systems**

- Remote Methane Leak Detector (RMLD, Sewerin)
  - exclusively developed for detecting methane gas, shows no cross-sensitivity to other hydrocarbons
  - detection principle
  - measurement specifications
  - laser specifications

---

Transceiver

Controller
## Optical Sensor Systems

- Remote Methane Leak Detector (RMLD, Sewerin)
  - exclusively developed for detecting methane gas, shows no cross-sensitivity to other hydrocarbons
  - detection principle
    - TDLAS (Tunable Diode Laser Absorption Spectroscopy)
  - measurement specifications
  - laser specifications
Optical Sensor Systems

- Remote Methane Leak Dector (RMLD, Sewerin)
  - exclusively developed for detecting methane gas, shows no cross-sensitivity to other hydrocarbons
  - detection principle
  - measurement specifications
  - laser specifications
2. Optical Sensor Systems
   - Remote Methane Leak Detector (RMLD, Sewerin)
     » exclusively developed for detecting methane gas, shows no cross-sensitivity to other hydrocarbons
     » detection principle
     » measurement specifications
     » laser specifications
       • class 1 laser (no eye protection required)
       • conical beam, width 0.56 m at 30 m
Mobile Robot Olfaction

Key Contributions
Mobile Robot Olfaction

Key Contributions

Not today 😊
Gas Distribution Mapping

Selected Ongoing Work
Gas Distribution Mapping
Computation of Turbulent Gas Distribution?
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
4. **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

\[
p(r_* \mid \bar{x}_*, \bar{x}_{1:n}, r_{1:n})\]

- gas prediction
- query location
- measurement locations
- gas measurements

[Lilienthal et al., ECMR 2007]
Gas Distribution Mapping

Kernel DM+V
4. Kernel DM+V

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

![Diagram showing 1D example with artificial data and two blue curves representing the kernel density estimation between two points \( x_*(1) \) and \( x_*(2) \).]
1D Example – Artificial Data (180 data points)

- Kernel DM+V → two intertwined estimation processes

[Lilienthal et al., IROS 2009]
4. **Kernel DM+V**

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

- **1D Example – Artificial Data (180 data points)**
  - Kernel DM+V ($\sigma = 0.75$)
<table>
<thead>
<tr>
<th>1D Example – Artificial Data (180 data points)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kernel DM+V ($\sigma = 3.0$)</td>
</tr>
</tbody>
</table>
4. Kernel DM+V

- 1D Example – Artificial Data (3900 data points)
  - Kernel DM+V ($\sigma = 0.75$)
4. Kernel DM+V

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

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

Multi-Compound Kernel DM+V
Robot and Sensors

- Pioneer P3-DX
- Two complementary in situ gas sensors
  - 5 MICS e2v MOX sensors (e-nose)
4. MC Kernel DM+V

**Robot and Sensors**
- Pioneer P3-DX
- two complementary in situ gas sensors
  - 5 MICS e2v MOX sensors (e-nose)
  - gas identification
### Robot and Sensors

- Pioneer P3-DX
- two complementary in situ gas sensors
  - 5 MICS e2v MOX sensors (e-nose) → gas identification
  - ppbRAE 3000 PID (Photo Ionization Detector)
### Robot and Sensors

- **Pioneer P3-DX**
- **two complementary in situ gas sensors**
  - 5 MICS e2v MOX sensors (e-nose)
    - gas identification
  - ppbRAE 3000 PID
    - (Photo Ionization Detector)
    - quantification of a known gas
### Robot and Sensors

- Pioneer P3-DX
- Two complementary in situ gas sensors
  - 6 MICS e2v MOX sensors (e-nose) → gas identification
  - ppbRAE 3000 PID (Photo Ionization Detector) → quantification of a known gas
### Environment

- 5 x 5 x 2 m³ closed room
- no artificial airflow
  - weak circulating airflow field
  - natural convection: 0.01-0.03 m/s
- two gas sources
  - ethanol
  - 2-propanol
  - constant release @ 0.2 l/min
  - distance between sources: 0.5m / 1.5m
- predefined trajectory
  - spiral trajectory
  - 30s stops at regularly spaced way points for data collection
4. MC Kernel DM+V
   - classification of gases in an open sampling system

[Trincavelli, IJCAI 2011]
[Trincavelli et al., ICRA 2010]
[Trincavelli et al., SAB 2009]
[Trincavelli et al., ISOEN 2009]
[Trincavelli et al., IROS 2008]
4. MC Kernel DM+V

- classification of gases in an open sampling system
  - Multi Variate Relevance Vector Machine (MVRVM)
  - autoregressive kernel for 30s time series input
    - parameters chosen by cross-validation
  - training with single source experiments

References:
- [Trincavelli, KI 2011]
- [Trincavelli et al., ICRA 2010]
- [Trincavelli et al., SAB 2009]
- [Trincavelli et al., ISOEN 2009]
- [Trincavelli et al., IROS 2008]
4. MC Kernel DM+V

- classification of gases
  in an open sampling system
  \[ \rightarrow \text{posterior of the sample being gas } 1, \ldots, l \]

- [Trincavelli, KI 2011]
- [Trincavelli et al., ICRA 2010]
- [Trincavelli et al., SAB 2009]
- [Trincavelli et al., ISOEN 2009]
- [Trincavelli et al., IROS 2008]
4. MC Kernel DM+V
   - classification of gases in an open sampling system
     - posterior of the sample being gas 1, ..., l
     - classification maps

[Hernandez Bennets et al., IEEE Sensors 2012]

maximum a posteriori plot
MC Kernel DM+V

- classification of gases in an open sampling system
  - sample posteriors (classification maps)
- compute mean map for each substance
  - use PID (apply calibration factor for each substance)

[Hernandez Bennets et al., IEEE Sensors 2012]
4. MC Kernel DM+V

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[ Hernandez Bennets et al., IEEE Sensors 2012]
**MC Kernel DM+V**

- classification of gases in an open sampling system
  - → sample posteriors (→ classification maps)
- compute mean map for each substance
  - use PID (apply calibration factor for each substance)
  - compute mean map

\[
C^{(k)}_l = \frac{\sum_{i=1}^{n} \mathcal{N}(\|x_i - x_k\|) \cdot \psi^i \cdot c_i}{\sum_{i=1}^{n} \mathcal{N}(\|x_i - x_k\|) \cdot \psi^i}
\]

\[
C_{l0} = \frac{\sum_{i=1}^{n} \psi^i \cdot c_i}{\sum_{i=1}^{n} \psi^i}
\]

\[
c_l^{(k)} = \alpha^{(k)} \cdot C_l^{(k)} + (1 - \alpha^{(k)}) \cdot C_{l0}
\]
### MC Kernel DM+V

- **classification of gases in an open sampling system**
  - → sample posteriors (→ classification maps)
- **compute mean map for each substance**
  - use PID (apply calibration factor for each substance)
  - compute mean map

\[
C_i^{(k)} = \frac{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k|) \cdot \psi_i^j \cdot c_i}{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k|) \cdot \psi_i^j}
\]

\[
C_{i0} = \frac{\sum_{i=1}^{n} \psi_i^j \cdot c_i}{\sum_{i=1}^{n} \psi_i^j}
\]

\[
c_{i}^{(k)} = \alpha^{(k)} \cdot C_{i}^{(k)} + (1 - \alpha^{(k)}) \cdot C_{i0}
\]

[Hernandez Bennets et al., IEEE Sensors 2012]
**MC Kernel DM+V**

- classification of gases in an open sampling system
  - \(\rightarrow\) sample posteriors \(\rightarrow\) classification maps
- compute mean map for each substance
  - use PID (apply calibration factor for each substance)
  - compute mean map

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C_l^{(k)} = \frac{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k|) \cdot \psi_i \cdot c_i}{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k|) \cdot \psi_i}
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- **MC Kernel DM+V**
  - classification of gases in an open sampling system
    - sample posteriors (classification maps)
  - compute mean map for each substance
    - use PID (apply calibration factor for each substance)
    - compute mean map

\[
C_i^{(k)} = \frac{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k| \cdot \psi_i^k \cdot c_i)}{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k| \cdot \psi_i^k)}
\]

\[
C_i^{(0)} = \frac{\sum_{i=1}^{n} \psi_i^k \cdot c_i}{\sum_{i=1}^{n} \psi_i^k}
\]

\[
c_i^{(k)} = \alpha^{(k)} \cdot C_i^{(k)} + (1 - \alpha^{(k)}) \cdot C_i^{(0)}
\]
4. MC Kernel DM+V
   - classification of gases in an open sampling system
     - sample posteriors (classification maps)
   - compute mean map for each substance
     - use PID (apply calibration factor for each substance)
     - compute mean and variance map
MC Kernel DM+V

- classification of gases in an open sampling system
  - → sample posteriors (→ classification maps)
- compute mean map for each substance
  - use PID (apply calibration factor for each substance)
  - compute mean and variance map

\[
V_l^{(k)} = \frac{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k| \cdot \psi_l \cdot (c_i - c_{i}^{(k)(i)})^2)}{\sum_{i=1}^{n} \mathcal{N}(|x_i - x_k| \cdot \psi_l)}
\]

\[
V_{l0} = \frac{\sum_{i=1}^{n} \psi_l \cdot (c_i - c_{i}^{(k)(i)})}{\sum_{i=1}^{n} \psi_l}
\]

\[
v_l^{(k)} = \alpha^{(k)} \cdot V_l^{(k)} + (1 - \alpha^{(k)}) \cdot V_{l0}
\]
Gas Distribution Mapping

3D GDM with Remote Gas Sensors
Robot and Sensors

- Husky A200 (Clearpath Robotics)
## Robot and Sensors
- Husky A200 (Clearpath Robotics)
- Remote Gas Sensor: TDLAS
  - Sewerin RMLD
4. Robot Gas Tomography

- Robot and Sensors
4. Environment

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. **Robot Gas Tomography**

- **Environment**
  - outdoor (near ORU campus)
    - remote controlled exploration of 154m² / 432m² area
  - gas source: flask of natural gas
    - flask connected to tube ring under permeable mat

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
### Environment

- **outdoor (near ORU campus)**
  - remote controlled exploration of 154m² / 432m² area

- **gas source: flask of natural gas**
  - flask connected to tube ring under permeable mat

- **measurements**
  - robot stopped to collect gas measurements
  - PTU → continuous sweeping movement, pan: (-70°; 70°), tilt: (-8°; -2°)
    - no artificial reflectors
    - RMLD always pointing towards the ground (grass surface)

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography
   • Approach
     o 3D Model Acquisition
       » NDT Fusion and Tracking → NDT-OM map
     o Gas Distribution Mapping
       » try to “explain” integral measurements
       • First results, outdoors
         • [Hernandez Bennets et al., ICRA 2014?]
         • [Hernandez Bennets et al., ICRA 2013]
**Approach**

- **3D Model Acquisition**
  - NDT Fusion and Tracking $\rightarrow$ NDT-OM map
    - tracking: NDT D2D registration
    - fusion: update NDT-OM

[![Hernandez Bennets et al., ICRA 2014?](image1)](image1)
[![Hernandez Bennets et al., ICRA 2013](image2)](image2)
[![Stoyanov et al., IROS 2013](image3)](image3)
[![Saarinen et al., IJRR 2013](image4)](image4)
[![Saarinen et al., IROS 2013](image5)](image5)
[![Stoyanov et al., IJRR 2012](image6)](image6)
4. Robot Gas Tomography

- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking $\rightarrow$ NDT-OM map $\rightarrow$ beam paths
  - Gas Distribution Mapping
    - try to "explain" integral measurements

\[
y = l_6 \cdot x_6 + l_{10} \cdot x_{10} + l_{11} \cdot x_{11} + l_{15} \cdot x_{15} + l_{16} \cdot x_{16} + l_{20} \cdot x_{20} + \epsilon
\]
4. Robot Gas Tomography

- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking $\rightarrow$ NDT-OM map $\rightarrow$ beam paths
  - Gas Distribution Mapping
    - try to "explain" integral measurements
    - collect measurement dataset

\[
y = \sum_{i=1}^{M} l_i x_i + \epsilon \rightarrow y = Lx + \epsilon 1
\]

- $M =$ Number of cells traversed by the beam
- $l_i =$ Distance travelled by the bean in cell $i$
- $x_i =$ Concentration in cell $i$
- $\epsilon =$ Measurement noise term
- $y =$ Integral concentration measurement

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
### Approach

- **3D Model Acquisition**
  - NDT Fusion and Tracking $\rightarrow$ NDT-OM map $\rightarrow$ beam paths

- **Gas Distribution Mapping**
  - try to "explain" integral measurements
  - collect measurement dataset
  - cast as optimization problem

\[
y = Lx + \varepsilon 1
\]

\[
\text{minimize} \quad \|Lx - y\|_2 + \lambda \|x\|_2
\]

subject to $x \geq 0$

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography

- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking $\rightarrow$ NDT-OM map $\rightarrow$ beam paths
  - Gas Distribution Mapping
    - try to "explain" integral measurements
  - First results, indoors

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography

**Approach**

- 3D Model Acquisition
  - NDT Fusion and Tracking → NDT-OM map → beam paths
- Gas Distribution Mapping
  - try to "explain" integral measurements
- First results, indoors

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking → NDT-OM map
  - Gas Distribution Mapping
    - try to "explain" integral measurements
  - First results, outdoors
ICRA 2013 😊

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography

- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking $\rightarrow$ NDT-OM map
  - Gas Distribution Mapping "2.0"
    - try to "explain" integral measurements

- [Hernandez Bennets et al., ICRA 2014]
- [Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography

- **Approach**
  - 3D Model Acquisition
    - NDT Fusion and Tracking → NDT-OM map
  - Gas Distribution Mapping "2.0"
    - try to "explain" integral measurements

\[
\begin{align*}
\text{minimize} \quad & \| Lx - y \|_2^2 + \lambda \| x \|_2^2 \\
\text{subject to} \quad & x \geq 0
\end{align*}
\]
4. **Approach**

- **3D Model Acquisition**
  - NDT Fusion and Tracking → NDT-OM map

- **Gas Distribution Mapping "2.0"**
  - try to "explain" integral measurements
  - estimate mean and variance

\[
\begin{align*}
\text{minimize} & \quad \| Lx - y \|_2^2 + \lambda \| x \|_2^2 \\
\text{subject to} & \quad x \geq 0
\end{align*}
\]

\[
S^2 = \frac{r^T r}{N - M}
\]

\[
r = y - L\hat{x}
\]

[Hernandez Bennets et al., ICRA 2013]

[Hernandez Bennets et al., ICRA 2014?]
Results

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
4. Robot Gas Tomography

- Results

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
Results

[Hernandez Bennets et al., ICRA 2014]
[Hernandez Bennets et al., ICRA 2013]
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
5. **Breakthroughs Needed!**

- **Evaluation of MRO systems**
  - 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

- **MRO community rather small**
  - Difficult to enter the field of MRO. Even large groups abandon the subject after a few simple tests/publications.
  - establish an accepted simulation environment
  - provide benchmark data sets
  - establish evaluation processes and the corresponding Open Source tools
Future Work

- 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 (include physics)
5. Future Work

- 3D perception / 3D gas sensing
  
  » develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches

- 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
Future Work

- 3D perception / 3D gas sensing
  - develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches
- Wind distribution models
  - Gas perception must build and integrate wind distribution models.
- 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
Future Work

- 3D perception / 3D gas sensing
  - Develop dense 3D modeling approaches and ways to take the spatial model into account.

- Wind distribution models
  - Gas perception must build and integrate wind distribution models.

- 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.

- Sensor planning
  - Under-sampling is generally prevalent in environmental monitoring.
  - Sensor planning: adaptive sampling with high density where required.
5. Future Work

- 3D perception / 3D gas sensing
  - Develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches.

- Wind distribution models
  - Gas perception must build and integrate wind distribution models.

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

- Sensor planning
  - Sensor planning: adaptive sampling with high density where required.

- 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.
5. Future Work

- 3D perception
  - Develop dense 3D modeling approaches and ways to take the spatial model into account in gas perception approaches

- Wind distribution models
  - Gas perception must build and integrate wind distribution models.

- 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

- Sensor planning
  - Adaptive sampling with high density where required

- Sensors for gasbots
  - Develop new sensors tailored for open sampling systems on a robot

- Flying gasbots
  - Superior mobility makes multicopters promising for MRO
  - Study interaction with gas distributions to minimize disturbance
Future Work

- 3D perception / 3D gas sensing
  - Develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches

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  - Gas perception must build and integrate wind distribution models.

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### Future Work

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  - Develop dense 3D modelling approaches and ways to take the spatial model into account in gas perception approaches.

- **Wind distribution models**
  - Gas perception must build and integrate wind distribution models.

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

- **Sensor planning**
  - Sensor planning: adaptive sampling with high density where required.

- **Sensors for gasbots**
  - Develop new sensors tailored for open sampling systems on a robot.

- **Flying gasbots**
  - Study interaction with gas distributions to minimize disturbance.
Future Work – New Applications
Future Work – New Applications
Acknowledgement

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Thanks!
Mobile Robot Olfaction

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