Integrating SLAM and Gas Distribution Mapping (GDM) – A Rao-Blackwellisation Approach to GDM/SLAM

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Applications of Gas Distribution Modelling
1 Gas Distribution Modelling

Applications

- Oil Refinery Surveillance
1 Gas Distribution Modelling

Applications

- Oil Refinery Surveillance
- Garbage Dump Site Surveillance
1 Gas Distribution Modelling

Applications

- Oil Refinery Surveillance
- Garbage Dump Site Surveillance
- Pollution Monitoring

- air quality monitoring and surveillance of pedestrian areas
- communicating pollution levels to technical staff / pedestrians
1 Gas Distribution Modelling

Applications

- Oil Refinery Surveillance
- Garbage Dump Site Surveillance
- Pollution Monitoring
  - air quality monitoring and surveillance of pedestrians
  - communicating pollution levels to technical staff
- Disaster Prevention
1 Gas Distribution Modelling

Applications

- Oil Refinery Surveillance
- Garbage Dump Site Surveillance
- Pollution Monitoring
  - air quality monitoring and surveillance of pedestrian areas
  - communicating pollution levels
- Disaster Prevention
- Rescue Robots
- ...
Gas Distribution Mapping in Natural Environments – The Challenges
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
  - diffusion
  - advective transport
  - turbulence
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
- Point Measurement
  - sensitive sensor surface is typically small (often $\approx 1\text{cm}^2$)
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
- Point Measurement
  - sensitive sensor surface is typically small (often $\approx 1\text{cm}^2$)
  - effective sampling region also small and approx. spherical (fan)
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
- Point Measurement
- Sensor Dynamics
Related Work on
Gas Distribution Mapping
3 Related Work on GDM

Approaches to GDM

- simultaneous measurements at equidistant grid positions with multiple stationary sensors
  - average concentration
  - average time 5 to 8 minutes


- peak concentration
- sampling period 20 s

3 Related Work on GDM

- Approaches to GDM
  - stationary sensor response → bi-cubic interpolation
    - consecutive measurements, averaging over 2 min
  - measurements in a wind tunnel

3 Related Work on GDM

Approaches to GDM

- mobile sensor → triangle-based cubic interpolation
  - sensor array carried by a robot, speed ≈ 10 cm/s, zig-zag trajectory


- measurements in a wind tunnel
- measurement points not equally distributed
- averaging over three runs
3 Related Work on GDM

Approaches to GDM

- odour hits histogram
  - gas sensor measurements from a group of robots (random walk)
  

- needs definition of a threshold, odour hits if larger than $\varepsilon$
  → map depends on $\varepsilon$

- wind tunnel experiment ($\approx$1m/s)

- hot water pan gas source and conducting polymer sensors
  → very fast sensor characteristic
3 Related Work on GDM

- Approaches to GDM
  - Kernel Gas Distribution Mapping
    - gas sensor measurements from a moving robot
    - interpret gas sensor measurements $z^{1:t}$ as random samples from a time-constant distribution
      - assumes time-constant structure of the gas distribution
      - randomness due to concentration fluctuations (measurement noise negligible)
    - kernel models information content of single readings
      \[ E[p(m_{gas}^{av} \mid x^{1:t}, z_{gas}^{1:t})] \]

3 Related Work on GDM

- Approaches to GDM
  - Kernel Gas Distribution Mapping
    - pre-defined path, random movement
    - metal-oxide gas sensors
      → long decay time
3 Related Work on GDM

Approaches to GDM

- position of the measurement points
  - from odometry
  - human measurements
  - external positioning system

- these approaches assume perfect knowledge of sensor positions
Integrating SLAM and Gas Distribution Mapping
5 Integrating SLAM and Gas Distribution Mapping

- General SLAM problem

\[ p(x_{1:t}^{|t}, m^t | u_{1:t}^{|t}, z_{1:t}^{|t}) \]

- simultaneously estimate the map and the robot path given robot actions \( u \) and observations \( z \)

- Simultaneous Localisation and Gas Distribution/Occupancy Mapping (GDM/SLAM)

\[ m \leftarrow m = \begin{pmatrix} m_{av}^{gas} \\ m_{occ} \end{pmatrix} \]

\[ z_t \leftarrow z_t = \begin{pmatrix} z_{gas,t} \\ z_{occ,t} \end{pmatrix} \]
5 Integrating SLAM and Gas Distribution Mapping

- The GDM/SLAM Problem
  - useful factorization if maps can be analytically estimated given a robot path hypothesis

\[
p(x^{1:t}, m^t | u^{1:t}, z^{1:t}) =
\]

\[
p(x^{1:t} | u^{1:t}, z^{1:t}) p(m^t | x^{1:t}, u^{1:t}, z^{1:t})
\]

- estimate robot path using a particle filter
- compute maps analytically

Rao-Blackwellization, Rao-Blackwellized Particle Filter (RBPF)
5 Integrating SLAM and Gas Distribution Mapping

- GDM/SLAM – Map Computation
  - observations $z_{occ}$ and $z_{gas}$ are conditionally independent
  - assume independency between $m_{occ}$ and $m_{gas}$
5 Integrating SLAM and Gas Distribution Mapping

- **GDM/SLAM – Map Computation**
  - observations $z_{occ}$ and $z_{gas}$ are conditionally independent
  - assume independency between $m_{occ}$ and $m_{gas}$
  - computing maps separately for each particle
    - mapping using known poses
    - occupancy grid map using sensor integration
      [Moravec/Elfes 1985]
    - gas distribution grid map using
      kernel based gas distribution mapping [Lilienthal/Duckett, 2004]
5 Integrating SLAM and Gas Distribution Mapping

- GDM/SLAM – Estimation of the Robot Path
  - sample from the motion model
    \[ x_t^{[i]} \sim p(x_t \mid x_{t-1}^{[i]}, u_t) \]
  - update weights with the observation model
    \[ \omega_t^{[i]} \propto \omega_{t-1}^{[i]} p(z_t \mid x_t^{[i]}, m^{[i]}) \]
  - higher weights for particles that correspond better with the current observations
5 Integrating SLAM and Gas Distribution Mapping

GDM/SLAM – Estimation of the Robot Path

observation model

\[ p(z_t | x_t^{[i]}, m^{[i]}) = p(z_{\text{gas},t}, z_{\text{occ},t} | x_t^{[i]}, m_{\text{gas}}^{[i]}, m_{\text{occ}}^{[i]}) \]

\[ = p(z_{\text{gas},t} | x_t^{[i]}, m_{\text{gas}}^{[i]}) p(z_{\text{occ},t} | x_t^{[i]}, m_{\text{occ}}^{[i]}) \]

\[ \approx \eta p(z_{\text{occ},t} | x_t^{[i]}, m_{\text{occ}}^{[i]}) \]

use only the laser scanner to estimate the path
5 Integrating SLAM and Gas Distribution Mapping

Computing the ML Estimate of the Maps

- computed as the marginal of the maps taken over all the hypotheses of robot paths

\[ p(m \mid z^{1:t}) = \sum_i \omega_t^{[i]} p(m \mid x^{1:t, [i]} , z^{1:t}) \]

- assuming that Kernel-GDM approximates

\[ E[p(m_{gas}^{av} \mid x^{1:t, [i]}, z_{gas}^{1:t})] \]

the final GDM estimate is

\[ \sum_i \omega_t^{[i]} E[p(m_{gas}^{av} \mid x^{1:t, [i]}, z_{gas}^{1:t})] = E[p(m_{gas}^{av} \mid z_{gas}^{1:t})] \]
Experiments and Results
6 Experiments

Service Robot Sancho

- base: Pioneer 3DX
- laser range finder: SICK LMS 200
- pair of e-noses
6 Experiments

Service Robot Sancho
- base: Pioneer 3DX
- laser range finder: SICK LMS 200
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Electronic Nose
- 4 metal-oxide gas sensors (Figaro): TGS 2600 [x2], TGS 2602, TGS 2620
- sensors in a tube with CPU fan
- sampling frequency: 1.25 Hz
- separation: 14 cm; height: 11 cm
6 Experiments

- Environment
  - University of Malaga, Computer Science building
  - one indoor and one outdoor corridor
  - no modification for the experiment

- Gas Source
  - evaporating ethanol
  - robot could drive over the source (cup, height = 6 cm)
6 Results

- Result – SLAM
  - robot speed: 5 cm/s
  - trajectory: sweeping

max. likelihood path

robot speed: 5 cm/s
6 Results

- Result – Gas Distribution Map
  - lighter shading $\leftrightarrow$ higher concentration
  - different shading color for values $> 90\%$ of the max.
6 Results

- Result – Gas Distribution Map
  - lighter shading ↔ higher concentration
  - different shading color for values > 90% of the max.
6 Results

ML Estimate of the Gas Distribution Map

\[
\sum_i \omega_t^{[i]} E[p(m_{gas}^{av} | x^{1:t,[i]}, z_{gas}^{1:t})] = E[p(m_{gas}^{av} | z_{gas}^{1:t})]
\]
Summary and Future Work
Summary

- probabilistic framework for simultaneous localization and (occupancy) mapping and gas distribution mapping
  - Rao-Blackwellized particle filter formulation for GDM/SLAM
  - accounts for the position uncertainty when computing the gas distribution map
  - allows to plug in different GDM algorithms
Summary

- Conceptual framework to integrate kernel-based gas distribution mapping and SLAM
- Large gas distribution map (20 x 2 m²)
Future Work

- skip assumption that the gas distribution map and the occupancy grid map are independent
- model influence of obstacles on the gas distribution
7 Summary and Future Work

Future Work

- skip assumption that the gas sensor likelihood
  
  \[ p(z_{gas,t} | x_t^{[i]}, m_{gas}^{[i]}) \]

  is constant over the peak area
  of the occupancy observation likelihood

  \[ p(z_{occ,t} | x_t^{[i]}, m_{occ}^{[i]}) \]

  \[ \rightarrow \] exploiting the time-averaged gas distribution for localisation
A Rao-Blackwellisation Approach to GDM/SLAM – Integrating SLAM and Gas Distribution Mapping (GDM)

Thank you!