Integrating SLAM into Gas Distribution Mapping

Achim Lilienthal, Amy Loutfi
AASS, Dept. of Technology, Örebro University

Jose Luis Blanco, Cipriano Galindo and Javier Gonzalez
System Engineering & Automation Dept., University of Malaga
Gas Distribution Mapping + SLAM

position, position uncertainty
Contents

1. Applications of Gas Distribution Modelling?
2. The Challenges for Gas Distribution Mapping
3. Kernel Based Gas Distribution Mapping
4. Integrating SLAM and Gas Distribution Mapping
5. Experiments and Results
6. Summary
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 pedestrian areas
  - 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
- ...

Achim J. Lilienthal
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
- Sensor Dynamics
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
- 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
2 Gas Distribution Mapping – Challenges

- Chaotic Gas Distribution
- Point Measurement
- Sensor Dynamics
- Calibration

- Real-Time Gas Distribution Mapping
  - changes at different time-scales
    - rapid fluctuations
    - slow changes of the overall structure of the average distribution
Kernel Based
Gas Distribution Mapping
3 Kernel Based Gas Distribution Mapping

- General Gas Distribution Mapping Problem
  - given the robot trajectory $x^{1:t}$
  
  \[ p(m_{gas} \mid x^{1:t}, z_{gas}^{1:t}) \]

- Differences to Range Sensing
  - calibration: readings do not correspond directly to concentration levels
3 Kernel Based Gas Distribution Mapping

- General Gas Distribution Mapping Problem
  - given the robot trajectory \( x^{1:t} \)

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

- Differences to Range Sensing
  - readings don't correspond directly to concentration levels
  - chaotic gas distribution: an instantaneous snapshot of the gas distribution contains little information about the distribution at other times
3 Kernel Based Gas Distribution Mapping

- **General Gas Distribution Mapping Problem**
  - given the robot trajectory $x^{1:t}$

  $$p(m_{gas} \mid x^{1:t}, z_{gas}^{1:t})$$

- **Differences to Range Sensing**
  - readings don't correspond directly to concentration levels
  - instantaneous gas distribution snapshots contain little information about the distribution at other times
  - **point measurement**: a single gas sensor measurement provides information about a very small area ($\approx 1\text{cm}^2$)
3 Kernel Based Gas Distribution Mapping

Time-Averaged Gas Distribution Mapping Problem

- given the robot trajectory $x^{1:t}$

$$p(m_{gas}^{av} \mid x^{1:t}, z_{gas}^{1:t})$$

Kernel Based Gas Distribution Mapping

- interpret gas sensor measurements $z^t$ as random samples from a time-constant distribution
- assumes time-constant structure of the observed gas distribution
- randomness due to concentration fluctuations (measurement noise negligible)

3 Kernel Based Gas Distribution Mapping

- Analogy to Density Function Estimation
  - estimate the PDF of a random variable (Parzen window)

\[
\hat{p}_{PW}(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\|x - x_i\|; \sigma\right)
\]

- \( K \leftarrow 2D \) univariate Gaussian

from Duda, Hart, Stork "Pattern Classification"
Integrating SLAM and Gas Distribution Mapping
4 Integrating SLAM and Gas Distribution Mapping

- General SLAM problem

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

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

- Simultaneous Localisation and Gas Distribution / Occupancy Mapping ("GasSLAM")

\[ m \leftarrow m = \left( m_{\text{gas}}, m_{\text{occ}} \right) \]

\[ z_t \leftarrow z_t = \left( z_{\text{gas},t}, z_{\text{occ},t} \right) \]
4 Integrating SLAM and Gas Distribution Mapping

The GasSLAM Problem

- general approach: inverse sensor model to estimate maps
4 Integrating SLAM and Gas Distribution Mapping

The GasSLAM Problem

useful factorization if maps can be analytically estimated given a robot path hypothesis

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

$$p(x^{1:t} | u^{1:t}, z^{1:t}) p(m^t | x^{1:t}, u^{1:t}, z^{1:t})$$

estimate robot path compute maps
using a particle filter analytically

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

GasSLAM – Map Computation

- observations $z_{occ}$ and $z_{gas}$ are conditionally independent
- assume independency between $m_{occ}$ and $m_{gas}$
4 Integrating SLAM and Gas Distribution Mapping

GasSLAM – 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
  - occupancy grid map using sensor integration
    [Moravec/Elfes 1985]
- determine max. likelihood estimate of the maps from the weighted average (using particle weights)
GasSLAM – 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 better correspond with the current observations
GasSLAM – Estimation of the Robot Path

observation model

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

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

use only the laser scanner to estimate the path
Experiments and Results
5 Experiments

Service Robot Sancho

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

- Service Robot Sancho
  - base: Pioneer 3DX
  - laser range finder: SICK LMS 200
  - pair of e-noses

- 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
5 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)
5 Results

Result – SLAM

- robot speed: 5 cm/s
- trajectory: sweeping

max. likelihood path

20 m
5 Results

- Result – Gas Distribution Map
  - lighter shading $\leftrightarrow$ higher concentration
  - different shading color for values $> 80\%$ of the max.
5 Results

- Result – Gas Distribution Map
  - lighter shading $\leftrightarrow$ higher concentration
  - different shading color for values $> 80\%$ of the max.
Summary
5 Experiments

Summary

- conceptual framework to integrate kernel based gas distribution mapping and SLAM
5 Experiments

Summary

- conceptual framework to integrate kernel based gas distribution mapping and SLAM
- large gas distribution map (20 x 2 m²)
5 Experiments

Summary

- conceptual framework to integrate kernel based gas distribution mapping and SLAM
- large gas distribution map (20 x 2 m$^2$)
- uncontrolled environment
- combined indoor / outdoor environment
Integrating SLAM into Gas Distribution Mapping

Thank you!