## **Semaine 3**

Projet de Fin d'Etude / Master Thesis

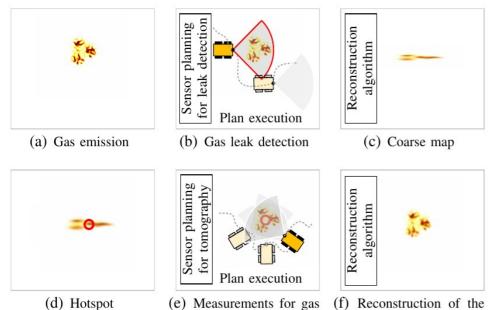


Fig. 1. Emission monitoring scenario with a mobile robot considered in this paper. Gas emission (a) is detected executing the *sensor planning algorithm* for gas detection, see [2] (b). A coarse gas distribution map is generated with the robot assisted gas tomography algorithm, see [3] (c), and a hotspot is identified in the coarse map (d). Next, a sensing geometry is planned using the *sensor planning algorithm for tomography*, which is the contribution of this paper (e). Finally, we obtain a high quality reconstruction using again the robot assisted gas tomography algorithm in [3] (f).

emission

tomography

- Objective: detect gas leaks, build gas distribution map
- Process: Fig.1
- TDLAS sensor: do not get distribution of gas along lineof-sight: Fig.2

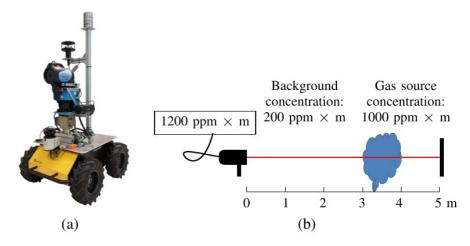


Fig. 2. (a) Gasbot robot is equipped with an actuated TDLAS sensor. (b) TDLAS sensor reports integral concentration of methane along its line-of-sight (ppm  $\times$  m).

- Contribution: optimization algorithm for sensor planning considering sensing geometries
- Sensing geometry = number of measurement locations + sensor pose = set of sensing configurations performed by a robot at a given area: \$c\_i = (p\_i, \phi\_i, r\_i)\$: Fig.3

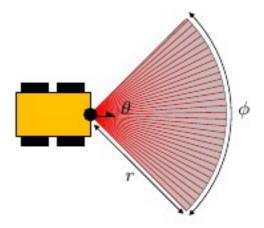


Fig. 3. A sensing action is the sampling of a circular sector  $(\phi, r)$  by emitting s optical beams.

- Sensing geometries simulation: 3 sensing geometries:  $\frac{1}{n_c^2} = \frac{2}{n_c^2} = \frac{3}{n_c^2} = \frac{4}{s}$
- Sensing geometries surrounding area of interest
- $\phi = [90^\circ, 180^\circ], r = 15m \text{ and } \Delta s = 1^\circ$
- Varying parameters: distance from area of interest (5m, 7m, 15m), \$||n\_c||\$, angular distance between 2 sensing configurations, gas concentration model (1<sup>st</sup>: high concentration in center of area of interest, other different).

• \$||n\_c|| = 4\$ does not improve results

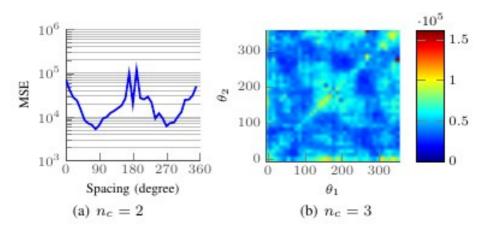


Fig. 5. (a) The mean squared error (MSE) between the ground truth and its reconstruction is shown for the set of 2 configurations ( $n_c = 2$ ). On the x-axis is the angular displacement between the configurations and on the y-axis is the MSE. The least reconstruction error and therefore highest reconstruction quality can be observed for cross angles of  $90^{\circ}$ . (b) The MSE is shown in the color code on the right for the set of 3 configurations ( $n_c = 3$ ). Along x-axis is the pair-wise angular displacement between the configurations 1 and 2 ( $\theta_1$ ), and along y-axis is the pair-wise angular displacement between the configurations 1 and 3 ( $\theta_2$ ). The results suggest that the reconstruction quality is best when pair-wise cross angles are  $60^{\circ}$  and  $120^{\circ}$  on a half circle.

 Exploration time = sensing time + traveling time

 Cost of set of \$k\$ configurations:

$$cost(\pi) = \sum_{i=1}^{k-1} t_{p_i \to p_{i+1}}^m + t_{p_k \to p_1}^m + \sum_{c_i \in \pi} t_{c_i}^s$$
 (1)

where  $t_{p_i \to p_{i+1}}^m$  is the time for the movement from pose  $p_i$  to  $p_{i+1}$ ,  $t_{p_k \to p_1}^m$  to close the loop and  $t_{c_i}^s$  is the sensing time of configuration  $c_i$ .

Optimal set of configurations:

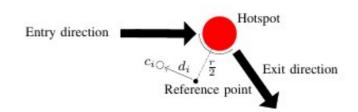
$$\pi_{opt} = \operatorname*{argmin}_{\pi_i \in \Pi} cost(\pi_i) \text{ s.t. } ERQ \ge \mathfrak{n}$$
 (2)

## Algorithm 1 xvt-SPP

- 1: Identify high concentration regions (hotspots);
- Solve TSP for the hotspots (and start position) to approximately determine entry and exit directions of the robot for each hotspot;
- For each hotspot, find a sensing geometry with maximum ERQ (Eq. 5) taking into account entry and exit direction;
- Combine the local sensing configurations by removing overlapping redundant configurations (Eq. 7);
- Solve TSP for the configurations and the start position to find a tour;
- Execute tour and apply the tomographic reconstruction algorithm [11] to build GDM;
- 7: OPTIONAL: Identify high concentration region(s) and go back to step 2 to refine the GDM;

- Gas detection prior step to get high concentration regions on a map (inaccurate)
- $\mathbb{E} \mathbb{R} \mathbb{Q} \mathbb{G}$ :  $G_{n_c=3} = \sum_{\forall \mu \in M} 0.5 e^{\frac{-(A-\mu)^2}{2\sigma^2}}, \ \sigma = 10^{\circ}, M = \{60^{\circ}, 120^{\circ}\}$
- Hotspot used to define cross angles. But also sensing coverage of areas with gas concentration above threshold, visible from configuration \$c\$

- \$C\$ = vector of candidate configurations
- \$D\$ = vector of distances of the travel time from the reference point to each sensing configuration.
- ERQ for the cross angles is \$C'GC\$ and the sensing coverage is \$VC\$



## Optimisation problem:

maximize 
$$\alpha C'GC + (1 - \alpha)C'U$$
 (5a) subject to

$$\mathbf{1}'C \le n \tag{5b}$$

$$C \in \{0, 1\}$$
 (5c)

$$U = \beta(\overline{\mathbf{1}'V}) + (1 - \beta)(1 - \overline{D})) \tag{6}$$

 If hotspots are far from each other, connect them with TSP. Else high probability of similar configurations for different hotspots → fusion → optimisation problem:

$$\begin{array}{ll}
\text{minimize} & |C| \\
\text{subject to}
\end{array} \tag{7a}$$

$$ZC \succeq \mathfrak{g} - \delta$$
 (7b)

$$C \in \{0, 1\}$$
 (7c)

Strategies for Optimal Placement of Surveillance Cameras in Art Galleries (Marcelo C. Couto, Cid C. de Souza, Pedro J. de Rezende, Jun. 2014)

- AGP NP-Hard
- Polygon P with n vertices
- N/3 cameras are sufficient
- Cameras on vertices, 360° field of view
- Discretisation of P into a finite set of points D(P)
- Solve SCP (Integer Programming)

Strategies for Optimal Placement of Surveillance Cameras in Art Galleries (Marcelo C. Couto, Cid C. de Souza, Pedro J. de Rezende, Jun. 2014)

- Discretisation startegies:
  - Regular Grid
  - Induced Grid: grid induced by the edge extensions that intersect in the polygon.
  - Just Vertices: grid consisting only of the vertices of P
  - Reduced Atomic Visibility Polygons: reduction of Atomic Visibility Polygons

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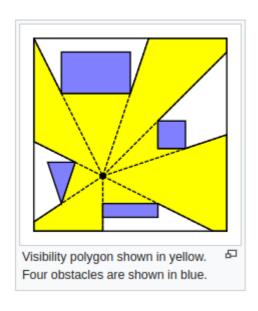


Table 1: Results for Complete von Koch polygons.

	Final $ D(P) $			Total Time		
# vertices	20	100	500	20	100	500
Reg. Grid	45	500	6905	0.05s	1.57s	92.37s
Ind. Grid	24	205	1665	0.03s	1.41s	70.94s
Red. AVPs	28	324	5437	0.07s	3.14s	143.93s
Just Vert.	20	107	564	0.04s	0.97s	29.35s