Sniffing out fugitive methane emissions: autonomous remote gas inspection with a mobile robot

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Abstract
Air pollution causes millions of premature deaths every year, and fugitive emissions of, e.g., methane are major causes of global warming. Correspondingly, air pollution monitoring systems are urgently needed. Mobile, autonomous monitoring can provide adaptive and higher spatial resolution compared with traditional monitoring stations and allows fast deployment and operation in adverse environments. We present a mobile robot solution for autonomous gas detection and gas distribution mapping using remote gas sensing. Our “Autonomous Remote Methane Explorer” (ARMEx) is equipped with an actuated spectroscopy-based remote gas sensor, which collects integral gas measurements along up to 30 m long optical beams. State-of-the-art 3D mapping and robot localization allow the precise location of the optical beams to be determined, which then facilitates gas tomography (tomographic reconstruction of local gas distributions from sets of integral gas measurements). To autonomously obtain informative sampling strategies for gas tomography, we reduce the search space for gas inspection missions by defining a sweep of the remote gas sensor over a selectable field of view as a sensing configuration. We describe two different ways to find sequences of sensing configurations that optimize the criteria for gas detection and gas distribution mapping while minimizing the number of measurements and distance traveled. We evaluated an ARMEx prototype deployed in a large, challenging indoor environment with eight gas sources. In comparison with human experts teleoperating the platform from a distant building, the autonomous strategy produced better gas maps with a lower number of sensing configurations and a slightly longer route.

Keywords
Environmental monitoring, autonomous exploration, remote gas inspection, mobile robot olfaction, fugitive methane emissions.

1. Introduction
The carbon gap between current emissions and the commitment in the Paris Agreement to avoid dangerous global warming is widening (Christensen and Olhoff, 2019). Consequently, it has become more challenging to keep an increase in global average temperature below 2 °C above the pre-industrial level. In 2019, the major greenhouse gases carbon dioxide (CO₂) and methane (CH₄) accounted for 72% and 19% of global emissions, respectively, using a 100-year Global Warming Potential basis (Olivier and Peters, 2020).

Unlike carbon dioxide, methane is extremely flammable and can form an explosive mixture with air. On the other hand, methane is a hydrocarbon that can be used as a cleaner source of energy than other fossil fuels, e.g., coal (Alvarez et al., 2012). It is also used as an ingredient to manufacture fertilizers (e.g., nitro-phosphate and calcium ammonium nitrate) and the importance of monitoring methane emissions produced by the ammonia fertilizer industry has been pointed out recently (Zhou et al., 2019). In a nutshell, methane emission monitoring is important for three reasons: (1) its climate impact, (2) the associated safety risks, and (3) its economic importance. Fossil fuel production and landfill are among the major sources of human-caused fugitive methane emissions (Forster et al., 2007; Holmgren et al., 2015), and monitoring systems are needed to reduce emissions in those areas.
A monitoring system requires sensing technologies and approaches to sample the environment and extract information about areas with increased methane concentration and the presence and location of gas sources to take necessary actions. An efficient monitoring system should also be cost-effective, easy to deploy, and flexible enough to provide adaptive sampling that takes into account previous gas measurements and changing environmental parameters.

Gas sensors can be categorized into *in situ* and remote sensors. *In situ* sensors provide local measurements of gas concentrations and, thus, require a high number of sampling points or strong prior assumptions that must be made in order to estimate dense distribution models (Fraden, 2010). In contrast, remote sensors with a large sensing range require fewer sampling configurations (Mikel et al., 2011). In our work, we use tunable diode laser absorption spectroscopy (TDLAS), which emits an optical beam with a wavelength that is tuned to an absorption band of the gas molecule of interest. It returns spatially unresolved integral concentrations along the line of sight. TDLAS is very selective and generally responds to its target gas only, even in the presence of multiple airborne substances.

In an area in which a gas leak is suspected, a human operator could carry a remote gas sensor and walk through the area to perform the gas inspection. However, there are a number of problems with this approach: (1) it can be a dangerous task due to the presence of explosive or toxic gases; (2) it is a laborious and tedious work for a human operator to perform systematic sampling; and (3) without having the necessary tools of analysis to localize the gas measurements accurately or to build a gas distribution model, it is difficult to understand gas emissions from the set of measurements. On the other hand, a robot carrying a remote gas sensor can perform these tasks comprehensively and repeatedly. The robot can be equipped with methods to estimate gas distributions and hotspot areas accurately, for example, using gas tomography – a procedure to estimate the spatial distribution of gas concentrations from a set of integral gas measurements. The gas tomographic approach can model gas distributions in contained gas sources as well as complex gas plumes of freely escaping gas. In addition to detailed analysis and estimation of hotspot areas, the reconstructed gas distribution can also be used to quantify leak flux, which is difficult for a human operator looking at the integral measurements only.

In this article, we focus on a mobile robotic system with remote gas sensing and the capability of performing autonomous gas operations. Accordingly, we call this system Autonomous Remote Methane Explorer (ARMEx). We use the TDLAS sensor “Remote Methane Leak Detector” (RMLD), which does not require a dedicated reflector for collecting measurements. The reflectance of the floor or any reflective surface in the environment is sufficient, and there is no significant loss of accuracy depending on the reflective surface. In the system we propose, the RMLD is actuated with a pan-tilt unit (PTU) to sample the environment inside an adjustable field of view and, thus, to cover a large area without actually being in direct contact with gaseous emissions. A typical inspection requires to sample the environment at different locations to detect gas leaks and build an accurate gas distribution model on which the gas sources can be located, see Figure 1. A mobile platform provides several advantages over a traditional, stationary sensor network. It enables flexible sensor placement to collect more measurements in areas of interest than in low concentration areas and allows the use of a single or a few expensive sensors to monitor large environments, for example.

The advantages of flexible sensor placement carried out by mobile robots come with new challenges, however. These challenges include (1) a need to accurately locate the measurements as the sensor is carried along by the mobile platform, (2) to navigate the sensor between different sampling locations, (3) measurement strategies are needed to sample the environment *efficiently*, for example with minimum operational time, (4) that the overall robotic solution must be applicable not only in small scale test environments, but also in large-scale, complex environments.

To address these challenges, we equip our robot with commercially available sensors and existing algorithms that enable it to localize and move autonomously between different sensing locations in the environment. To allow for fully autonomous operation, we developed and implemented optimization-based sensor planning algorithms that decide sensing configurations for the detection of high-concentration areas, and an accurate estimation of gas distributions using a detailed tomographic reconstruction in the gas detection areas. All components were selected or developed for real-world operation, and the system was validated in large, complex, real-world environments.

Our work is guided by two research questions.

**Research Question 1.**

How to plan efficient gas inspection missions for an autonomous mobile robot equipped with an actuated remote gas sensor? [RQ1]

**Research Question 2.**

How does the autonomous gas inspection system fare compared with human experts teleoperating the robot for the inspection mission? [RQ2]

In line with these overarching research questions, the major contributions of this work are as follows.

[1] An autonomous solution for remote gas inspection with a mobile robot → [RQ1]

We are proposing ARMEx, an autonomous solution for gas inspection using an actuated remote gas sensor on a mobile robot. Our goal is to build an accurate gas distribution map (GDM) of the environment, which can be used for detailed analysis or to locate gas sources. We perform fully autonomous gas sampling for the inspection tasks of gas detection and gas distribution mapping under the assumption that the robot has access to the geometric map of the environment. The prior map of the environment is also used to visualize the inspection process.
We have designed and implemented sensor planning algorithms that select optimal sensing configurations for remote gas inspection. For the gas detection task, we solve a full sensing coverage problem in two phases, which we have reported previously in Arain et al. (2015a): first, to find a near-optimal solution for a minimal set of sampling poses and then to solve a traveling salesman problem (TSP) using existing approaches (Applegate et al., 2006) to find the shortest traveling distance between the selected sampling poses. Upon detection of hotspots, we set out to perform detailed gas tomography for accurate gas distribution mapping. Our sensor planning algorithm for gas mapping finds informative sampling poses of overlapping sensing coverage with different viewpoints to accurately reconstruct the gas distribution. The initial version of this algorithm is presented in Arain et al. (2016) and fundamentally improved in this article: a new procedure is developed for the estimation of the areas of interest (hotspots); improved multi-criteria weights for candidate measurement configurations; and the optimization problem is formulated to select a minimal set of measurement configurations for the desired reconstruction quality.

A straightforward approach for gas inspection, which we used in our previous work (Arain et al., 2016), is to carry out two subsequent robotic tours, one for the initial gas detection and the second for gas distribution mapping (two-tour mission strategy, 2t-ARME\text{X}). In particular, for inspection in large environments, gas detection and gas distribution mapping should not be performed in separate phases to be efficient. This article presents a new adaptive strategy that combines both tasks in a single robotic tour (one-tour adaptive mission strategy, 1t-ARME\text{X}). The strategy interleaves the initially planned exploration for gas detection each time a high concentration is detected with a detailed tomographic reconstruction for gas distribution mapping. After that, the gas detection plan is updated for the remaining uncovered areas.

**Evaluation compared with human experts**

Autonomous gas inspection has certain advantages over manual operation: performing a long-term task is a boring and tedious job for a human operator; deciding optimal sensing configurations in a complex environment is difficult; telepresence may add additional difficulties when the operation has to be performed in a dangerous area. We evaluate the performance of our autonomous remote sensing system against the strategies of human experts teleoperating the robot. The human experts who participated are experienced in developing gas-sensing systems, building gas maps, and conducting field experiments.

We introduced the evaluation of autonomous gas-sensing systems against human experts for the first time in Arain et al. (2016). However, in those experiments, only
one human expert participated who had to decide all the sensing configurations for a single robotic tour of gas distribution mapping in advance, i.e., without having access to updated gas maps during the inspection. Selecting sensing poses for a human operator is a method of teleoperating a robot. Teleoperation experiments have also been performed for gas source localization in Gongora and Gonzalez-Jimenez (2019). However, the experiments were conducted by inexperienced operators using a mobile robot with in situ gas sensors and visual feedback, and no comparison with an autonomous system was performed. In this article, we have developed a user interface that facilitates human experts to decide one sensing configuration at a time. The operation can be visualized (in our experiments without live streaming of a camera so that the gas sources cannot be recognized in the video), and the human experts can inspect intermediate tomographic reconstructions to estimate gas source locations and determine the next sensing pose.

The experimental evaluation is carried out to investigate the following: (1) as a proof of concept of ARMEx, an autonomous gas inspection with a mobile remote sensor; (2) since the general architecture of ARMEx can also be used in a non-autonomous way, we show that the developed system is flexible enough to be used in both type of missions, autonomous and teleoperation; and (3) to analyze the system performance in terms of solution costs and quality. We performed six experiments in a complex real-world indoor environment of size $120 \times 30$ m$^2$. In each of the experiments, two autonomous operations were performed using our two mission strategies, and a teleoperation mission was conducted by one of the human experts. The experimental results show that the autonomous system consistently generated better gas maps, correctly located more gas sources, and provided better sensing coverage compared with human experts.

3] Gas inspection in relatively large environments → [RQ1, RQ2]

We further bring gas-sensing mobile robots from environment sizes that require about half an hour of operation to large-scale, complex environments that require several hours of operation. To the best of the authors’ knowledge, autonomous gas-sensing robots have not previously been tested at such a scale. The important limiting factors for large-scale operations are sensing range and finding optimal sampling configurations in large search spaces. In ARMEx, we use an actuated remote gas sensor to cover a large field of view, and design efficient sensor planning algorithms that can quickly find near-optimal solutions. In our current setting, the on-board battery power is primarily a defining factor for the maximum operation time, which is a hardware limit.

2. Related work

An environmental monitoring system (EMS) is used to sample atmospheric variables of interest to observe, study, and derive knowledge about the environment. A common approach is to use a stationary sensor network for pollution monitoring (Barrenetxea et al., 2008; Prud’homme et al., 2013; Tsujita et al., 2005), ventilation characterization (Sherman, 1990), and measurement of atmospheric gas concentrations (Somov et al., 2012, 2011; Zhou et al., 2009). Mobile robots in environmental monitoring were introduced in 2000 (Guccione et al., 2000; Whitcomb, 2000), and a more recent example of pollution monitoring and ventilation characterization with mobile robots and stationary networks can be found in Hernandez Bennetts (2019); Hernandez Bennetts et al. (2016).

Emission of greenhouse gases is a critical environmental aspect (Solomon et al., 2010) and, correspondingly, airborne chemical sensing of greenhouse gases is an important EMS application of mobile robots. The inspection tasks of a gas-sensing mobile robot can include gas detection, gas discrimination in a mixture of gasses, gas quantification, gas distribution mapping, and gas source localization (Hernandez Bennetts, 2015). The use of drones is one possible approach to the problem (Golston et al., 2018; Neumann et al., 2019; Oberle et al., 2019; Yang et al., 2018). Drones have better mobility than most ground robots and can be easily deployed in open environments. In comparison, the mobility of ground vehicles is affected by difficult terrain. However, the operation time of drones is typically much shorter than that of ground robots, which limits their usability to perform detailed gas tomography in large areas or makes it necessary to deploy swarms of drones. We are interested in relatively long time operations and want to build high-resolution GDMs in large areas for detailed analysis. Moreover, we assume that the gas, if present, can be detected near the ground level. This assumption applies to many real-world applications: for instance, methane leaks on a landfill necessarily occur close to the ground.

Traditionally, in situ gas sensors are considered for gas-sensing applications of mobile robots, for example, for statistical gas modeling (Hernandez Bennetts et al., 2011; Li et al., 2016; Lilienthal et al., 2009; Monroy et al., 2016) and searching for gas sources (Albertson et al., 2016; Monroy et al., 2018; Moraud and Martinez, 2010; Von Fischer et al., 2017; Zhang et al., 2015). Recent developments in gas-sensing technologies have made it possible to use remote gas sensors on mobile robots with certain advantages. We consider an actuated remote gas sensor to sample a large area inside a field of view, without being visited by the robot. In the following discussion, we compare our proposed solution with the other ground robot-based remote gas-sensing solutions.

Mobile robots equipped with a remote gas sensor have been reported for gas leak detection (Baetz et al., 2009; Kroll et al., 2009), gas distribution mapping using a tomographic algorithm (Hernandez Bennetts et al., 2013), and combined remote gas sensing with thermal imaging for gas leak detection in Soldan et al. (2014). The systems described by Baetz et al. (2009), Soldan et al. (2014), and
Kroll et al. (2009) use the same remote gas-sensing technology along with a mobile robot as we do in ARME\textsuperscript{x}; however, they are basically designed for the inspection of a pipeline or related industrial equipment only. Their task is to find a leak inside a vertical window, at predefined inspection configurations.

We consider optical beams projected along the horizontal plane for ground-level gas detection. This means the beams are not necessarily reflected at the leak points, and they can travel a considerable distance after the leak points. Therefore, instead of using a tri-max window to locate the leak along a vertical plane (Bonow and Kroll, 2013), we perform gas tomography (Price et al., 2001) to accurately model the concentration distribution in a 2D environment, along the horizontal plane. Moreover, we do not assume predefined sensing configurations for gas inspection as in Soldan et al. (2014). Instead, we let the robot decide sensing configurations.

The initial concept of our current robotic solution was introduced in Hernandez Bennetts et al. (2014), evolved through Arain et al. (2015a) and Arain et al. (2016), and into the complete autonomous inspection that we present and evaluate in this article. We first introduced measurement planning for a mobile robot equipped with a remote gas sensor (Arain et al., 2015b). We have designed different sensor planning algorithms to enable the robot to select near-optimal sensing configurations for the inspection tasks of gas detection and gas distribution mapping.

We cast gas detection as a full sensing coverage problem. If we approximate the sensing coverage of an actuated remote gas sensor with a camera-like field of view, then several related sensor placement approaches can be found in the areas of known problems: art gallery problem (Lee and Lin, 1986), view planning problem (Scott, 2009), set covering problem (Erdem and Sclaroff, 2006), covering salesman problem (Golden et al., 2012), or traveling view planning problem (Wang et al., 2007a,b). Further detail on related work and our sensor planning algorithm for gas detection can be found in Arain et al. (2015a).

The task of gas distribution modeling using gas tomography requires to sample the area of interest with an overlapping sensing coverage of different viewpoints (Byer and Shepp, 1979). We have presented an initial version of our sensor planning algorithm for gas distribution mapping in Arain et al. (2016), which we believe is the only available sensor placement approach for gas distribution mapping using gas tomography. In this article, we make fundamental changes in the algorithm: we develop a new procedure for the estimation of hotspots; use new results for the evaluation of sensing geometries (Arain et al., 2017); improve multi-criteria weights for candidate measurement configurations; formulate the optimization problem to select a minimal set of measurement configurations for the desired reconstruction quality.

Another contribution in this article is a new one-tour mission strategy (1t-ARME\textsuperscript{x}) that switches from gas detection to gas distribution mapping each time a high concentration is detected during a single tour to perform an efficient inspection mission. The strategy uses a sensor planning algorithm for gas detection, presented in Arain et al. (2015b); and a sensor planning algorithm for gas distribution mapping, the fundamentally improved version presented in this article.

3. Autonomous Remote Methane Explorer

This section describes the system in detail and an implementation of ARME\textsuperscript{x} that was then used to perform an experimental evaluation as a proof of concept. In the following sections, first, we discuss the assumptions we make and our design choice for ARME\textsuperscript{x} (Section 3.1), and then we describe the four major components of our system: (1) actuated remote gas sampling at a particular pose using the gas sensor mounted on a PTU to collect integral measurements within a set field of view (Section 3.2); (2) the robot navigation, which requires the robot to be localized and a path planned between different sensing locations in the environment (Section 3.3); (3) the gas tomography algorithm to build a model of the gas distribution using localized integral measurements (Section 3.4); and (4) measurement planning for autonomous inspection to decide optimal sensing configurations of desired performance criteria for gas detection and gas distribution modeling (Section 4).

3.1. System design and assumptions

We use a mobile robot equipped with a remote gas sensor to perform gas inspection tasks. A drone or ground robot can carry a remote gas sensor to map the environment along the ground. A drone with a downwards pointing remote gas sensor (Oberle et al., 2019; Yang et al., 2018) can fly over the area to collect integral measurements along the vertical axis, as illustrated in Figure 2(a). However, this approach will provide only sparse, effectively point measurements with a significant risk of missing small gas patches. High-resolution gas mapping thus becomes even more challenging in addition to the short operation time of drones.

The downwards pointing remote gas sensor on a drone can be actuated to project optical beams in different directions in a field of view (Neumann et al., 2019) (see Figure 2(b)). Thus, the necessary number of configurations at which the drone takes measurements to cover the area can be reduced. In that case, a high number of optical beams of different ground-track lengths need to be projected at each sampling point to cover the area inside the field of view for high-resolution gas mapping. The maximum sensing range along the horizontal plane will also be reduced as the sensor is elevated using a drone.

Instead, we propose to use a ground robot with an actuated remote gas sensor to perform gas tomography, as shown in Figure 2(c). The optical beam projected along the horizontal plane can detect freely escaping gas along its path. In this way, a larger area inside the field of view can
be covered than by a drone operating at a higher altitude, and the necessary number of measurement configurations can be further reduced. If, on the other hand, we consider an actuated remote gas sensor on a drone that can also be placed near ground level and can perform gas sampling by projecting optical beams along the horizontal plane, the approach described in our article is equally applicable and using a drone instead of a ground robot would only introduce disadvantages due to the shorter operation time and downwash interference with gas distributions.

As we target applications of ground-level gas sensing, detection of low concentrations from small leak points at, for example, a landfill site is more probable with a ground robot than a drone owing to dense area coverage for the same number of measurements inside a field of view. We thus consider in this article a ground robot carrying an actuated remote gas sensor to perform hours of operation in large environments. The conceptual diagram of ARMEx is shown in Figure 3. The corresponding experimental validation of the system was carried out with an implementation based on a Husky A200 robot, see Figure 4.

The remote gas sensor is actuated to collect gas measurements within a defined field of view, near ground level. Moreover, the environment in which gas inspection is to be carried out is expected to be a flat surface with or without obstacles, which allows the movement of a ground vehicle robot. To simplify the problem and make it tractable, we assume that the measurements are collected at discrete poses, disregarding the possibility to collect gas measurements while the robot moves from one sensing pose to the next due to possible localization errors of the projected optical beams. We also assume that the robot can localize itself and plan an obstacle-free path between goal poses in the area. Since the remote gas sensor provides spatially unresolved integral measurements with no information about the length of the projected optical beams, we also assume that a geometric map of the environment can be used to estimate the beam lengths using, for example, a ray-casting technique. In this way, the localized integral gas measurements can be used as an input to a tomographic reconstruction algorithm to build a GDM and to localize the gas sources.

An important problem is to decide where the robot should sample the environment. Teleoperation can be performed by a human operator sitting outside the inspection area and deciding the sampling poses for the robot. However, it is a difficult yet dull job for an operator to efficiently plan the next sampling pose(s) based on, for example, all the collected measurements and a given map of the environment. To allow for completely autonomous missions, we present and evaluate sensor planning algorithms that aim at optimizing performance criteria for gas detection and gas distribution mapping while minimizing the number of measurements and the total distance traveled. Moreover, to efficiently complete the gas inspection in large environments, we design mission strategies above the sensor planning algorithms to decide, using all information available at a particular time, when to perform which inspection task.

3.2. Actuated remote gas sampling

We consider gas inspection with remote gas sensors, which can acquire integral concentration measurements by calculating the interaction of gaseous particles and electromagnetic energy emitted from an artificial source (active...
sensors). Absorption spectroscopy (Mikel et al., 2011) is a well-known principle behind most active sensors. Among different absorption spectroscopy technologies, TDLAS sensors are very specific to a target gas. They are accurate, relatively lightweight, and do not require frequent maintenance (Mikel et al., 2011).

In our design of ARMEx, we consider a TDLAS sensor that can be mounted on a mobile robot. Figure 5 shows an RMLD sensor, which can collect integral concentration measurements along a beam of up to 30 m length. The sensor does not require a dedicated reflector as the reflectance of the floor or any reflective surface in the environment is typically sufficient without a significant loss of measurement accuracy. The RMLD detects background methane in the atmosphere, which is typically 2 ppm (Green et al., 2005) and accordingly contributes up to 60 ppm/C1 m of background concentration for a projected optical beam of 30 m lengths.

Using a remote gas sensor poses certain challenges, however. The RMLD, for example, neither provides Navigation sensor(s)
Remote gas sensor (RMLD)
Actuated remote gas sampling
Estimation of beam length
Reconstruction algorithm
Robot Localization
Path Planning
Measurement planning strategies
Gas distribution map
Gas source localization
Current gas map
Current pose
Goal pose
Actuator (PTU)
Sensing action
Actuation command
Integral gas measurements
Gas distribution map
Gas source localization

Fig. 3. A conceptual diagram of the ARMEx system for autonomous inspection with a remote gas sensor. A mobile robot is equipped with a remote gas sensor (RMLD) that can collect spatially unresolved integral gas measurements along its optical beam. The sensor is actuated with a PTU to sample the area inside an adjustable field of view at a given pose. In this manner, the robot can perform gas sampling being placed at different sensing locations in the environment (Section 3.2). We assume that the robot has access to environment map(s) that can be used along with existing algorithms for localization and path planning to navigate between desired sensing locations (Section 3.3). We also assume that the environment map(s) can be used to estimate the projected beam lengths of the remote sensor. This is required for the tomographic reconstruction of a GDM, which is described in Section 3.4. The key contributions of this article are measurement planning strategies for autonomous inspection by a mobile robot equipped with a remote gas sensor. The strategies aim at optimizing performance criteria for gas detection and gas distribution mapping while minimizing the number of sensing configurations and traveling distance using our sensor planning algorithms (Section 4).

Fig. 4. A conceptual diagram of the ARMEx system for autonomous inspection with a remote gas sensor. A mobile robot is equipped with a remote gas sensor (RMLD) that can collect spatially unresolved integral gas measurements along its optical beam. The sensor is actuated with a PTU to sample the area inside an adjustable field of view at a given pose. In this manner, the robot can perform gas sampling being placed at different sensing locations in the environment (Section 3.2). We assume that the robot has access to environment map(s) that can be used along with existing algorithms for localization and path planning to navigate between desired sensing locations (Section 3.3). We also assume that the environment map(s) can be used to estimate the projected beam lengths of the remote sensor. This is required for the tomographic reconstruction of a GDM, which is described in Section 3.4. The key contributions of this article are measurement planning strategies for autonomous inspection by a mobile robot equipped with a remote gas sensor. The strategies aim at optimizing performance criteria for gas detection and gas distribution mapping while minimizing the number of sensing configurations and traveling distance using our sensor planning algorithms (Section 4).

Fig. 4. Hardware of the ARMEx implementation used in this article. The conceptual diagram in Figure 3 shows a corresponding functional view on the ARMEx system. All the system components interact with each other using the Robot Operating System (ROS).
information about the concentration distribution along the reflected beam, nor the length of the beam. We assume that the robot has access to an environment map, which can be used with the localized RMLD pose to estimate the beam length using ray-casting. The problem of estimating the concentration distribution from localized integral measurements (tomographic reconstruction) is discussed in Section 3.4.

The onboard remote sensor in ARMEx is mounted on an actuated PTU so that the sensor can be rotated along pitch and yaw to sample the area inside a given field of view. The optical beam of the remote sensor must be projected on the ground to reflect the signal back to the sensor for gas measurements. The length of an optical beam is determined as the distance between the origin of the beam and the point of reflection. Thus, in case a PTU is used to actuate the sensor, the tilt angle ($\theta_{\text{tilt}}$) must be adjusted to obtain the desired sensing range (Figure 6(a)), and the sensor must be rotated along the pan-axis, i.e., $\theta_{\text{pan}} = \pm \phi / 2$ (Figure 6(b)), to sample the area inside an angle of view $\phi$. In our implementation, we used a Sewerin RMLD$^2$ remote sensor and a Schunk PW-70$^3$ PTU.

![Fig. 5. Illustration of integral measurement with the RMLD. The sensor projects an optical beam to measure a 518 ppm-m integral concentration, of which 500 ppm-m is due to the gas source and 18 ppm-m is due to the background concentration. It should be noted that (1) the sensor indicates only spatially unresolved integral measurements that do not include information about a gas source location or, generally, the concentration distribution along the beam, and (2) the sensor that we use does not report the actual length of the optical beam. Thus, the concentration distribution has to be estimated from a set of measurements using tomographic reconstruction, which requires determining the length of the optical beams.](image)

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![Fig. 6. (a) The remote sensor (RMLD) is rotated along the tilt axis of the PTU, and the projected optical beam is reflected after hitting the ground. The length of an optical beam $r$ is the distance between the origin of the beam and the point of reflection. (b) A sensing sweep is performed by rotating the sensor along the pan axis of the PTU for the given angle of view $\phi$.](image)

Fig. 6. (a) The remote sensor (RMLD) is rotated along the tilt axis of the PTU, and the projected optical beam is reflected after hitting the ground. The length of an optical beam $r$ is the distance between the origin of the beam and the point of reflection. (b) A sensing sweep is performed by rotating the sensor along the pan axis of the PTU for the given angle of view $\phi$.

3.3. Robot navigation

The robot is required to move autonomously between selected sensing configurations. Thus, ARMEx must be able to (1) plan an obstacle-free path, and (2) localize the robot to execute the plan successfully. We assume that the robot has access to geometric map(s) of the environment that can be used to plan a path, and has the necessary sensor(s) to localize itself and follow the planned path.

A commonly used environment representation is the occupancy grid map (OGM), which models the occupancy in a grid of binary random variables. In our implementation, we maintain an OGM using the approach of Grisetti et al. (2007), and we use a 2D robot navigation stack (Marder-Eppstein et al., 2010) for path planning.

The robot needs to localize itself to follow the planned path. In the experimental setup of ARMEx, we used a normal distribution transform (NDT) based mapping approach (Stoyanov et al., 2013), which models the environment as a sparse Gaussian mixture model and requires a significantly lower number of cells than OGM. The NDT-based Monte Carlo localization (NDT-MCL) approach (Saarinen et al., 2013) is used to localize the robot. The robot is equipped with a 2D-LiDAR (Sick LMS-151$^4$) and a 3D-LiDAR (Velodyne HDL-32E$^3$) for environment sensing to perform localization and plan execution. We utilize a heterogeneous representation of the environment (OGM and NDT map) for the simplicity of implementation.
main contributions in measurement planning to bring complete autonomy into ARMeX.

Further discussion is divided into three parts: the first part describes our assumptions, simplifications, and formulation of the measurement planning problem for the gas inspection missions; the second part is about our sensor planning algorithms that generate individual sensor placement solutions for the inspection tasks of gas detection and gas distribution mapping. We do not separately cast a sensor planning problem for gas source localization, but we use the generated GDM to estimate gas source locations; the last part describes our mission strategies to perform inspection tasks of gas detection and gas distribution mapping collectively and efficiently.

4.1. Problem formulation

We represent the environment in which the inspection mission is to be performed as a 2D Cartesian grid of occupied and unoccupied cells and formulate the problem of deciding sampling poses as a sensor placement problem. Occupied cells contain an obstacle and are considered (1) not traversable by the robot, and (2) to reflect the optical beam of the sensor before it can reach any other obstacle, typically the ground. This assumption may not strictly hold as the area corresponding to an occupied cell of a grid map may not be completely occupied in the real world. Thus, some occupied cells can be traversed by the robot, and for some, the optical beam of the sensor can pass through. However, the assumption that an occupied cell reflects the optical beam of the remote gas sensor is conservative for the validity of a measurement plan (as it may only lead to measure some of the cells, usually a small fraction, more often than necessary), and a fine grid map (cell size smaller than the robot length) will typically realistically capture the possibilities of sensor placement in the environment.

4.1.1. Sensing configuration. A sensing configuration corresponding to sampling the environment over a certain area by using an actuated remote gas sensor is defined as follows.

Definition 1. (Sensing configuration) A sensing configuration \( c \) is a prescribed sampling routine to cover a certain area with the actuated RMLD: a sensing configuration placed at pose \( (x, y, \theta) \) can potentially cover an adjustable field of view \( (\phi, r) \) of opening angle \( \phi \) and sensing range \( r \) by projecting \( s \) equally spaced optical beams inside the field of view, see Figure 8(a).

A candidate sensing configuration \( c_i \) is described by a hextuple \( (x_i, y_i, \theta_i, r_i, \phi_i, s_i) \): the robot pose \( (x_i, y_i, \theta_i) \), the field of view \( (\phi_i, r_i) \) of opening angle \( \phi_i \) and sensing range \( r_i \), and the number of projected optical beams \( s_i \). To reduce the search space in which sensing configurations are to be selected for a particular inspection task, we limit the number of candidate configurations by fixing the field of view.

4.4. Reconstruction of gas distribution

While the area is being inspected, the collected integral measurements are processed to create GDMs during or at the end of the operation. We perform a tomographic reconstruction on the measurements to generate a GDM, which is a spatial representation of gas concentration distribution in a grid. As the RMLD reports integral measurements with no information about the length of the beam, we localized the optical beam using the estimated robot pose and environment map.

The least-squares approach presented in Hernandez Bennetts et al. (2014) is used for tomographic reconstruction. The algorithm to estimate the gas concentration in a grid is framed as a convex optimization problem. The input to the algorithm is the set of localized integral measurements, which are collected with the remote gas sensor and the corresponding optical beam of each measurement is localized using the sensor pose (for the initial position) and ray-casting on the environment grid map (for the end position of the optical beam). The generated GDM is further used to locate gas sources. An example of the reconstruction process is shown in Figure 7.

4. Measurement planning for autonomous inspection

In an inspection mission, the robot needs to follow sampling poses that are either indicated by a human operator or a result of sensor planning algorithms. In the latter case, efficient algorithms are required to decide sensor placement. We consider the following tasks in a gas inspection mission: (1) gas detection, to sample the environment for initial detection of gas; (2) gas distribution mapping, to sample the environment for accurate modeling of gas concentration distribution; and (3) gas source localization, to estimate the location of gas sources, which we approach by using the generated GDM. In this section, we present our
Fig. 8. (a) A sensing configuration is a prescribed sampling routine. It can cover a selectable field of view \((\phi, r)\) of opening angle \(\phi\) and sensing range \(r\) at pose \((x, y, \theta)\). (b) Computation of sensing coverage provided by a sensing configuration. A candidate configuration is placed on a grid map, and due to obstacles, some of the cells in the circular sector cannot be covered. A cell is declared covered if a line segment connecting the configuration position to the center of the cell is within the circular sector and not intersected by any occupied cell. The observable cells for the configuration are marked gray.

\[ (\phi, r) \text{ and number of beams } s, \text{ and allowing the robot placement only at the center of unoccupied cells with discrete poses. The area inside a set field of view } (\phi, r) \text{ can be potentially covered using the actuated RMLD, and the terms } \phi \text{ and } r \text{ are fixed and independent of obstacles in the environment.} \]

**4.1.2. Sensing coverage.** Owing to obstructions, not all the cells in the circular sector \((\phi, r)\) of a candidate configuration are necessarily observable. We, therefore, define a visibility function \(v_{P}(c)\), which denotes the set of cells visible from \(c\). A cell \(k\) is considered visible to a sensing configuration \(c\) if the line segment connecting the centers of \(c\) and \(k\) is in the circular sector of \((\phi, r)\), and does not intersect any occupied cell, as shown in the example in Figure 8(b). In this way, we can capture sensing coverage of all the candidate configurations.

The optical beam of the sensor is of a conic shape and spreads out with increasing distance to its origin. In this way, the beam interacts with a larger cross-section of gaseous substance with increasing distance. A human operator inspecting the area is recommended to keep the RMLD sensor at a certain distance from the target, e.g., when searching for a point leak at a gas meter so that the beam footprint provides a large enough area coverage (Sewerin, 2015). A minimum distance requirement could be considered in the computation of sensing coverage. However, in our experiments, we did not observe problems with the detection of gas in close-by cells. This is probably because ARMEx performs systematic sampling by projecting a high number of equally spaced optical beams inside an adjusted field of view, which means that cells nearby the sensor are covered more densely.

**4.1.3. Measurement plan.** We define a measurement plan as a sequence of sensing configurations.

**Definition 2. (Measurement plan)**

A measurement plan \(\pi\) is an ordered, finite set of sensing configurations \(\pi = \{c_1, \ldots, c_n\}\).

A measurement plan is computed for an inspection task of either gas detection or gas distribution mapping. The plan is required to provide a particular type of sensing coverage, either in terms of total observation of the environment, or an overlapping sensing coverage in particular areas. There are two types of operational costs associated with a measurement plan: a sensing cost, which is determined as the number of sensing configurations to be executed and the cost of each sensing configuration; and a traveling cost, which is associated with the length of the path required for the robot to travel. An optimal measurement plan provides the desired sensing coverage for an inspection task with the lowest operational cost. The overall problem of minimal operational cost can be viewed as a combination of two NP-hard problems: the art gallery problem for minimal sensing cost (Lee and Lin, 1986) and the TSP (Applegate et al., 2006) for the minimal traveling path. Thus, minimizing the sensing and traveling costs at the same time is computationally intractable for realistic environments. We solve the problem in two steps: first, to find a minimal set of configurations for the desired sensing coverage and, then, the shortest traveling path among the selected configurations. In this fashion, a near-optimal solution can be found quickly, which we refer to as an efficient measurement plan.

We cast gas detection as an exploration task, in which gas patches are to be detected by selecting sensing configurations such that full coverage is provided. A measurement plan for gas detection is denoted as \(\pi_{gd}\). For accurate gas distribution modeling, a detailed gas tomography is required. The selected configurations for gas distribution mapping must provide a desired overlapping sensing coverage with different cross angles between the optical beams around the areas of interest. A measurement plan for gas distribution mapping is denoted as \(\pi_{gdm}\).

**4.2. Sensor planning for inspection tasks**

In this section, we provide details of our sensing planning algorithms to generate efficient measurement plans for gas detection \(\pi_{gd}\) and gas distribution mapping \(\pi_{gdm}\). An overview diagram is shown in Figure 9, which will also guide further discussion in this section. Moreover, a sample environment with simulated gas distribution is shown in Figure 10, which will be used to illustrate each of the steps related to sensor planning for gas inspection tasks.

**4.2.1. Gas detection planning**

We previously proposed an efficient sensor planning algorithm for gas detection (Arain et al., 2015a,b) that generates a measurement plan \(\pi_{gd}\) for
full sensing coverage such that any gas source can be detected from at least one sampling pose. The planned configurations in $\pi_{gd}$ are executed to collect localized integral gas measurements, which are then fed into a tomographic reconstruction algorithm (Hernandez Bennetts et al., 2014) to model gas distribution. We will call the resulting reconstruction a coarse GDM because the configurations were planned to achieve coverage but not overlaps. Following the sample environment in Figure 10, the measurement plan for gas detection is shown in Figure 11(a), and the coarse GDM obtained at the end of the plan execution is shown in Figure 11(b).

4.2.2. Gas distribution mapping planning. Intuitively, to create an accurate GDM, the areas of interest (hotspots) need to be sampled at viewpoints that provide a strongly overlapping sensing coverage. This can be done with randomly selected sampling poses as in Hernandez Bennetts et al. (2014), but that is not a very efficient approach. We need to study: (1) how to estimate the areas of interest or hotspots as accurately as possible from the coarse GDM; (2) to understand which arrangements of sensing configurations offer a higher-quality reconstruction of gas distributions; and (3) how to plan sensing configurations accordingly. In the following sections, we describe our contributions to these topics, which are summarized in Figure 12 (an extension of Figure 9 for GDM planning).

**Estimation of hotspots**

We define a hotspot as follows.

**Definition 3. (Hotspot)**

A hotspot is an area of interest for the suspected gas sources, where a detailed tomographic reconstruction is desired. The center of the estimated hotspot is denoted with $h_c$, and $H_c$ is a list of all $h_c$.

The hotspot estimation algorithm is defined as the following. First, all non-zero concentration estimates are grouped/clustered in connected components based on their distance to define the distinct hotspot areas that require a closer look. Next, for each hotspot area, its center is
determined around which overlapping sensing configurations are planned. We have developed a divide-and-combine procedure to estimate the hotspots. Figure 13 shows an example of estimating the hotspots from the coarse GDM in Figure 11(b).

In the divide phase, the regions that contain non-zero concentration distribution are divided based on their geometric layout. First, the disjoint regions are identified using agglomerative clustering (Khan and Luo, 2005), see Figure 13(b). Then, to ensure that all the disjoint regions can be covered with the given sensing range, regions that are too large are sub-divided. The sub-division is performed iteratively such that any region of length \( l \) larger than the sensing range \( r \) is divided into equal parts of \( \left\lfloor \frac{2l}{r} \right\rfloor \) regions (Figure 13(c)) using \( k \)-means clustering (Lloyd, 1982).

In the combine phase, weighted-mean points of the concentration distribution in the identified regions are computed (Figure 13(d)). The sum of all the weights \( w_c \) associated with the mean points is 1:

\[
\sum_{i} w_c[i] = 1. \tag{1}
\]

To perform an accurate tomographic reconstruction for gas distribution mapping, the overlapping sensing coverage needs to be focused on the high concentration spots, which are approximated by the weighted mean points. The high-concentration spots of two or more regions close to each other can be combined for a single sensor placement solution. Therefore, in an iterative fashion, pair-wise weighted-mean points closer than half of the sensing range are replaced by their center of mass, starting with the shortest distance (Figure 13(e)). In the final step, the weighted-mean points that belong to the regions of very low-concentration distribution are discarded. This can be decided based on the concentration weights of mean points and the total gas concentration in the corresponding region (Figure 13(f)). One straightforward option for the concentration weights is setting a fixed threshold value. However, when the environment is populated with an increasing number of gas sources, then a fixed threshold can discard true estimations owing to the normalization of region weights in (1). Thus, in our implementation, we set the weight threshold to \( \frac{1}{n} \), where \( n \) is an estimate of the number of gas sources by the total number of current mean points. For the second condition to discard the weighted-mean points based on the total gas concentration in the region, we heuristically set a threshold of 2,500 ppm. We discard a point if both the conditions are violated. The remaining weighted-mean points are stored in the list \( \mathcal{H}_c \).

Fig. 10. A sample environment with the simulated gas distribution. The environment with obstacles represents realistic scenarios, such as an indoor area with walls. The visibility of the environment requires viewing from different locations. Artificial time-invariant Gaussian-shaped local gas distributions are chosen to be challenging for gas mapping. The five gas sources with different concentrations create different gas distributions of regular and irregular shapes; the hotspot areas are in close vicinity and far apart; gas accumulation effects are also captured. This gas distribution example is used in the text to illustrate different sensor planning steps.

Fig. 11. (a) A sensor planning solution for gas detection in the sample environment (Figure 10). The selected configurations are marked with their pose, field of view, and sequence to visit. (b) The coarse gas map obtained from the measurements collected during the gas detection process.
In our previous work (Arain et al., 2016), hotspots were defined as the disjoint regions of non-zero concentrations (see Figure 13(b)), and center locations $h_c$ were simply estimated as Euclidean means. Accordingly, configurations with overlapping sensing coverage were planned around the geometric mean of the hotspots instead of the high-concentration mean point. In addition, identifying the hotspots based on disjoint regions only can lead to too large areas, which cannot be covered by limiting the number of selected configurations to the number of sensing overlaps. The presented technique is a better estimation because it considers both the sensing range for the maximum area length of a hotspot and concentration distribution to estimate the center location $h_c$ to make sure that the most interesting areas are focused when overlapping coverage is planned.

**Evaluation of sensing geometries**

We define a sensing geometry as follows.
Definition 4. (Sensing geometry)
A spatial arrangement of sensing configurations used for tomographic reconstruction.

To plan sensing configurations for accurate gas distribution mapping of hotspots, we need to know which sensing geometries are linked to better reconstruction results. To understand how different sensing geometries affect the reconstruction quality, we performed a simulation evaluation for a single hotspot of different gas distributions (Arain et al., 2017). We used a computational fluid dynamics (CFD)-based gas dispersal simulation setup (Fan et al., 2017) to generate different realistic gas distributions. To investigate sensing geometries, we evaluated: (1) how the number of overlapping configurations affects the quality of the reconstruction; and (2) what are the preferred cross angles between the optical beams of the configurations. For the evaluation of sensing geometries, a different number of configurations ($g_c = [2, 3, 4, 5]$) with different cross angles (relative angles between their orientations) were systematically placed on a concentric circle around the simulated gas distributions (hotspots) (see Figure 14).

For preferred sensing geometries, we define an expected reconstruction quality (ERQ) as follows.
The gas source.

Evaluation results of sensing geometries

Table 1.

| Geometry | $Q_{max}$ | Optimal pairwise cross angles |
|----------|-----------|------------------------------|
| $g_1$ = 2 | 0.63      | {59°}                        |
| $g_1$ = 3 | 0.78      | {54°, 108°}                  |
| $g_1$ = 4 | 0.85      | {39°, 78°, 116°}             |
| $g_1$ = 5 | 0.90      | {39°, 78°, 116°, 155°}       |

Definition 5. (Expected reconstruction quality)
The ERQ is inversely proportional to the reconstruction error, i.e., the error between the true and the reconstructed distributions.

The ERQ is expressed as an expectation value because, in many cases, the exact reconstruction error is hard to determine owing to a lack of ground-truth, for example, with freely discharging gas. In a gas inspection task, it is important to know gas concentration magnitudes and their spatial distributions. The ERQ captures two reconstruction errors: (1) the global error of the spatial reconstruction, computed as nearness (Todd and Ramachandran, 1994); and (2) the divergence of the probability density function (PDF) of the ground-truth and the reconstructed concentration map, computed as the Jensen–Shannon divergence (JS-div) (Lin, 1991). The ERQ is computed as an average of feature scaling for Nearness and JS-div in the range of [1, 0] for min–max values. The best results from the evaluation in Arain et al. (2017) are given in Table 1, which we use later in the sensor planning algorithm.

Sensor placement problem

With the estimated hotspots and the knowledge about preferable sensing geometries obtained in the study described in the previous section, the next step of sensor planning for GDM is to select an optimal sensing geometry that maximizes the ERQ for a given number of sensing configurations. In general, the sensor placement problem for gas distribution mapping is hard. We note here that the evaluation for sensing geometries presented in Arain et al. (2017) is limited: it was (1) carried out in simulation analyzing only about 0.4 million sensing geometries, (2) only a single hotspot with a limited amount of different gas distributions was considered, and (3) only sensing geometries with $g_1 = [2, 3, 4, 5]$ were analyzed. An evaluation of multiple hotspots at different possible locations and different gas distribution patterns is not feasible. Such studies should also consider sensing geometries with a higher number of configurations ($g_1 > 5$). Another reason why the sensor placement problem for gas distribution mapping is hard is that it includes a multi-criteria optimization problem.

We approach sensor planning for gas distribution mapping in two steps. First, optimal sensing geometries according to the desired ERQ are selected for each of the hotspots, individually. After that, all the selected geometries for the hotspots are fused into one global geometry to generate an overall measurement plan for high-quality tomographic reconstruction of the gas distributions. In the following sections, we describe: (1) how multi-criteria weights are defined for candidate sensing configurations; (2) how the optimal sensing geometries for the reconstruction of hotspots are selected; (3) how the sensing geometries for all hotspots are fused to obtain the final measurement plan ($\pi_{gdm}$); and (4) the evaluation for the selection of parameters for multi-criteria weights.

Multi-criteria weights for candidate configurations

The evaluation of preferable sensing geometries considered configurations aligned along a concentric circle around the actual hotspot center. However, in real-world environments with geometric constraints, it is not always possible that the configurations with the desired pairwise cross angles can be placed at all. We now also consider all candidate configurations that can cover the hotspot center, not only candidate configurations on a concentric circle around the hotspot center, as we did in the evaluation of sensing geometries. This means each candidate configuration can provide sensing coverage to the concentration distribution around different hotspots. We, therefore, formulate the sensor planning problem allowing for deviations from the preferred cross angles and from on-concentric-circle configurations to find the closest feasible approximation to preferred sensing configurations.

To select configurations that optimize multiple criteria, we define a unit interval gain $G$, which is directly proportional to ERQ and contains the combined information of cross angles and sensing coverage for the reconstruction. It also combines the traveling distance information, which does not directly affect the reconstruction quality, but a shorter traveling distance is preferred to minimize operational cost. The $G$ is computed in (7), which we describe in the following discussion. The obtained $G$ for a set of selected configurations can further be translated into the ERQ as

![Fig. 14. An instance of a $g_1 = 3$ sensing geometries evaluated in Arain et al. (2017). Simulated gas distribution in the middle is created using a CFD-based gas dispersal simulator. The configurations $c_1$, $c_2$, and $c_3$ are systematically placed with pairwise cross angles of $\theta_c$ and $2 \theta_c$ on a concentric circle around the gas source.](image-url)
and \(X\) with optimal cross angles number of configurations in the solution. The maximum series of overlapping Gaussian functions for the desired tions, a pair-wise unit interval gain

Table 1. ERQ for the given number of sensing configurations in

\[Q = G Q_{\text{max}},\]

where \(Q\) is the obtained ERQ and \(Q_{\text{max}}\) is the maximum ERQ for the given number of sensing configurations in Table 1.

For preferred cross angles between sensing configurations, a pair-wise unit interval gain \(\mathcal{X}\) is estimated using a series of overlapping Gaussian functions for the desired number of configurations in the solution. The maximum gain is associated with the pair of candidate configurations with optimal cross angles

\[\mathcal{X} = \frac{1}{n(n-1)} \max_{\mu \in M} \left( e^{-\frac{\delta^2}{2\sigma^2}} \right),\]

whereas

- \(\sigma = 20^\circ\), \(M = \{ 59^\circ \}\) for \(g_c = 2\)
- \(\sigma = 15^\circ\), \(M = \{ 54^\circ, 108^\circ \}\) for \(g_c = 3\)
- \(\sigma = 10^\circ\), \(M = \{ 39^\circ, 78^\circ, 116^\circ \}\) for \(g_c = 4\)
- \(\sigma = 10^\circ\), \(M = \{ 39^\circ, 78^\circ, 116^\circ, 155^\circ \}\) for \(g_c = 5\).

In (3), \(n\) is the number of configurations to be selected and \(\mathcal{X} = [0, 180]\) is a square matrix of pairwise cross angles between the candidate configurations. Here \(M\) is an array of mean values of Gaussian functions, see Table 1, and \(\sigma\) is the standard deviation obtained from the study of sensing geometries mentioned previously (Arain et al., 2017). The standard deviation for \(g_c = 2\) is highest, which means when only 2 configurations are to be selected, they can be placed with larger variations of cross angles compared with \(g_c = \{ 3, 4, 5 \}\). Similarly, configurations for \(g_c = 3\) can be placed with larger variations of cross angles than \(g_c = \{ 4, 5 \}\). The unit interval gain in (3) is divided by \(n(n-1)\) due to matrix multiplication in the final formulation of \(G\) for a hotspot ((7)). Figure 15 shows the function in (3) that models the pair-wise cross angle gain for a different number of configurations.

Although \(\mathcal{X}\) is used to express a preference for cross angles between the configurations, it is also required that a maximum sensing coverage is provided for the areas of high concentration. The unit interval sensing coverage gain \(\mathcal{V}\) is computed combining two factors: (1) the proportional coverage that describes the sum of gas concentration covered; and (2) the persistent coverage that describes the geometric arrangement of configurations around the hotspot. The proportional coverage \((P)\) in (4) captures the coverage of integrated concentration magnitudes in the cells covered by a candidate sensing configuration. The index \(P\) of a configuration \(c\) is computed as the sum of gas concentrations \(g\) (estimated from the coarse GDM) of all the cells covered. \(P\) is calculated as

\[P[c] = \sum_{\mathcal{V}} g[i].\]

The persistent coverage \((\mathcal{O})\) describes the geometric placement of a configuration concerning the hotspot. In particular, the field of view \((\phi, r)\) of a configuration must be concentric with the hotspot. This means, the point \((x + (r/2) \cos \theta, y + (r/2) \sin \theta)\) must be aligned with \(h_c\), where \(x, y, \theta,\) and \(r\) are the configuration parameters, see Figure 16. The persistent coverage gain \(\mathcal{O}\) is approximated with the two Gaussian functions for position and orientation offsets from \(h_c\). Given \(l\) as the distance between sensing position \((x, y)\) and \(h_c\), and \(\theta_h\) as orientation offset of sensing pose with \(h_c\), the index \(\mathcal{O}\) is computed as

\[\mathcal{O}[c] = \frac{1}{2} \left( e^{-\frac{-l^2}{2\sigma^2}} + e^{-\frac{-\theta_h^2}{2\sigma^2}} \right).\]

For the given proportional and persistent gains \(P\) and \(O\), the overall coverage gain \(\mathcal{V}\) is defined as

\[\mathcal{V} = \gamma P + (1 - \gamma) O.\]

Here we use the min–max normalized parameter \(\overline{P}\), keeping the minimum value at 0. The weight parameter \(\gamma = [0, 1]\) combines the two types of sensing coverages: a value close to 1 will prefer configurations with strong coverage of overall high concentration areas, and a value close to 0 prefer configurations that keep \(h_c\) in the middle of the circular sectors \((\phi, r)\) of the configurations.
In our previous work (Arain et al., 2016), only a count of cells covered by a candidate configuration, which contain gas concentration above a set threshold, was considered for the sensing coverage index. Consequently, entirely different gas distributions covered by two configurations could still be assigned the same coverage indices. The new approach computes a more useful sensing coverage index taking into account the concentration distribution covered and the geometric arrangement of the configurations around the hotspot. The evaluation for the parameter selection presented later in this discussion demonstrates that proportional and newly introduced persistent coverages are important criteria for improving reconstruction quality.

In addition to the cross angles and sensing coverage, we also consider traveling distance gain $\tau$ to prefer those configurations that correspond to a shorter traveling path. The details can be found in Arain et al. (2016).

Finally, $G$, the overall gain associated with a sensing geometry is defined in (7). It considers the pairwise cross angles gain $\chi$, the sensing coverage gain $\nu$, and traveling distance gain $\tau$. The weighting parameter $\beta = [0, 1]$ is used to combine $\chi$ and $\nu$, and the combination of $\chi$ and $\nu$ is further integrated with $\tau$ using another weighting parameter $\alpha = [0, 1]$. Altogether, we have three weighting parameters: $\gamma$ weighs between proportional (P) and persistent (O) coverages to obtain the overall sensing coverage $\nu$; then $\nu$ is weighted against pairwise cross angles $\chi$ using $\beta$; and finally, the combination of $\nu$ and $\chi$ are weighted against the traveling distance $\tau$ using the parameter $\alpha$. Hence, $G$ can be expressed as

$$G = \alpha \left( \beta C^T \chi C + (1 - \beta) C^T \nu \right) + (1 - \alpha) C^T \tau. \quad (7)$$

In (7), $C$ is a column vector, which contains binary decision variables representing if a given candidate sensing configuration is selected (value 1) or not (value 0). The parameters $\alpha$, $\beta$, and $\gamma$ are set heuristically to $\alpha = 0.95$, $\beta = 0.70$, and $\gamma = 0.20$. As the traveling distance does not directly affect the reconstruction quality, $\alpha$ is arbitrarily set to a high value to select configurations of preferred cross angles and sensing coverage, and only when two or more preferred configurations are of nearly the same cross angles and sensing coverage, then the one with the smaller traveling distance is selected. The values for $\beta$ and $\gamma$ were found using a set of simulation experiments with different real-world environment maps, discussed later in this section.

**Optimal sensing geometries for hotspots**

For a sensing geometry to be selected for a hotspot, candidate configurations are defined on the grid map, oriented towards $h_c$. The optimized solution of (7) for a given number $n$ of configurations is

$$\pi_{\text{hot}} = \text{argmax}_{C | \|C\| = 1} G \text{ s.t. } 1^T C \leq n. \quad (8)$$

The obtained $G$ can be used to compute the ERQ for hotspot ($Q_{\text{hot}}$) as in (2). The optimal sensing geometry for the reconstruction of a hotspot is selected by solving (8) iteratively. Starting with $n = 2$, one configuration is added in each iteration until the following conditions are true: (1) the obtained $Q_{\text{hot}}$ is smaller than the desired $Q_{\text{hot}}$; (2) $Q_{\text{hot}}$ is improved by more than 10% compared with the previous iteration; and (3) the number of selected configurations has not reached the upper limit of 5 (maximum number of configurations considered in the evaluation of sensing geometries). In our implementation, we used the Gurobi Optimization Solver to solve (8) and (9). Figure 17(a) shows the sensor placement solutions for the hotspots estimated in Figure 13.

**Fusion of the sensing geometries for hotspots**

The individually selected sensing geometries for each of the hotspots are now fused to obtain a global measurement plan. Straightforwardly selecting the union of all the configurations of the selected sensing geometries is a simple but not fully efficient approach: if two or more hotspots are close to each other (closer than twice the sensing range), some of the configurations in one sensing geometry can be very similar to configurations in the other sensing geometry. In such a case, a pair of redundant configurations can be replaced with a new configuration by keeping the desired ERQ of the corresponding hotspots. The candidate configurations for the replacement of redundant configurations are defined with orientations towards the geometric mean directions of the hotspots corresponding to the redundant configurations.

A list $L_p$ is created of all the pairs of potentially redundant configurations. This list is sorted in ascending order to their placement distance. For each pair of redundant configurations $l_p \in L_p$, we create another list $l_t$ that contains all the selected configurations in $\pi_{\text{hot}}$ of the corresponding hotspots $h_p \subseteq h_c$, except the configurations that are in the redundant pair $l_p$. The configurations in $l_t$ are fixed and cannot be replaced. At the beginning of the fusion process, each of the sensing geometries for a hotspot with fused configurations $\pi_{\text{hotfuse}}$ are set to as $\pi_{\text{hotfuse}} \leftarrow \pi_{\text{hot}}$. Then, an optimization procedure is formulated to solve the problem iteratively for each of the redundant pair $l_p$ as

$$\pi_{\text{hotfuse}} = \text{argmax}_{C | \|C\| = 1} \sum_{j \in [n]} G[j] \text{ s.t. } 1^T C \leq (|l_t| + 1) \quad (9)$$

and $C[k] = 1 \forall k \in l_t$.

$\pi_{\text{hotfuse}}$ in (9) is a valid solution if the obtained $Q_{\text{hot}}$ for hotspots in question $h_p$ is equal to or above the desired ERQ. In that case, the corresponding $\pi_{\text{hot}}$ are updated as $\pi_{\text{hot}} \leftarrow (\pi_{\text{hot}} - l_p)$ and $\pi_{\text{hot}} \leftarrow (\pi_{\text{hotfuse}} - l_t)$, i.e., by replacing the redundant configurations with the fused configuration. In each iteration, (9) is solved for the first pair in the list, and $L_p$ is updated either by removing the current pair from the list if the solution is not acceptable, or creating the list from scratch if the solution is acceptable. The
procedure continues until \( \mathcal{L}_p = \emptyset \), or the number of iterations is reached to a defined limit. In the end, the union of all the updated \( \pi_{\text{hotf}} \) is the fused solution:

\[
\pi_{\text{fuse}} = \bigcup_{j \in |\mathcal{N}|} \pi_{\text{hotf}}[j].
\]  

Figure 17(b) is the fusion of the sensing geometries for hotspots in Figure 17(a). For the given \( \pi_{\text{fuse}} \) and the initial pose \( p_0 \) of the robot, the configurations in the list are sorted to obtain the shortest traveling distance measurement tour by solving a TSP:

\[
\pi_{\text{gdm}} = f_{\text{exp}}(\pi_{\text{fuse}} \cup p_0).
\]  

Figure 17(c) shows the measurement plan for gas distribution mapping in the sample environment. The final GDM created after collecting gas measurements is shown in Figure 17(d), which is very similar to the simulated ground-truth distribution in Figure 10.

**Parameter selection for multi-criteria weights**

Simulated experiments were conducted to find the optimal values of the parameters, \( \beta \) and \( \gamma \). The environments are shown in Figure 18. The geometric maps used for the experiments are of real-world environments in which we carried out different mobile robot olfaction experiments in our previous work: (1) a campus corridor with stairs and sitting places (Arain et al., 2015a, 2016; Polvara et al., 2018; Vuka et al., 2017); (2) an outdoor forest area (Arain et al., 2015a; Hernandez Bennetts et al., 2013, 2014); (3) an industrial foundry where bronze bearings are produced (Schaffernicht et al., 2017); and (4) an industrial foundry where high-volume products are being cast (Hernandez Bennetts et al., 2016).

For the selection of parameters, simulations were performed in different layouts with artificial gas sources modeled as time-invariant Gaussian-shaped gas distributions. Note that, unlike in the evaluation of sensing geometries (Arain et al., 2017), we do not use CFD-based gas dispersal simulation here.

The parameters \( \beta \) and \( \gamma \) were defined in the range of \([0, 1]\) with an incremental step of 0.1, which results in a total of 121 experiments per test case. We designed 14 test cases (corresponding to a total of 1,694 experiments) in the four different environments. In each of the experiments, a different number of gas sources were placed at different
locations in the environment, and the measurement plans were generated to create the gas maps. The created maps were evaluated against the true concentration distributions to compute ERQ. Finally, a grid search in the reconstruction quality of the experiments concluded that setting $\beta = 0.7$ and $\gamma = 0.2$ can obtain the best ERQ values.

**Fig. 18.** The left and the right column show target real-world environments, in which we previously conducted different mobile robot olfaction experiments. In this article, the geometric maps created in the previous work are used in a simulation for the selection of the optimal values of the parameters $\beta$ and $\gamma$. The parameter $\beta$ is used to determine the relative weight of the cross angles gain $X$ in comparison with the sensing coverage gain $V$. The parameter $\gamma$ is used to determine the relative weight between the proportional sensing coverage gain $P$, and the persistent sensing coverage gain $O$. The maps shown in the middle column are manually cleaned low-resolution grid maps downsampled from OGMs of four different environments. A set of experiments was designed for the systematic combination of different parameter values of $\beta$ and $\gamma$, using different layouts of artificial gas sources to plan gas distribution mapping. The resultant GDMs of the experiments were evaluated and optimal values of $\beta = 0.7$ and $\gamma = 0.20$ were found.
4.3. Inspection mission strategies

The sensor planning algorithms for gas inspection tasks generate individual measurement plans for gas detection and gas distribution mapping. In particular, for a mission in large environments, both inspection tasks need to be performed efficiently as a whole. Thus, we need strategies that decide when to perform each task to complete the inspection mission most efficiently.

**Definition 6. (Mission strategy)**

We define a mission strategy as a decision-making strategy for measurement collection. We consider specifically the combined inspection tasks of gas detection and gas distribution in a gas inspection mission.

To carry out an autonomous inspection in large environments, we compare two mission strategies: (1) collect measurements in two subsequent robotic tours, one for gas detection and the other for gas distribution mapping processes; and (2) perform a gas inspection mission in a single robotic tour by collecting measurements in an interwoven fashion for both tasks (1t-ARME). The two-tour strategy is an offline planning approach considering robotic tours and computes a plan in the gas detection and the gas mapping round and then executes it, without updating the plan based on the information gathered during plan execution, as discussed in Section 4.2 and Figure 9. The 1t-ARME is an adaptive, one-tour approach that is presented in the following. It interleaves the initially planned exploration for gas detection with measurement sequences for a detailed tomographic reconstruction of the GDM each time a high concentration is detected. After performing gas mapping in the local region, the gas detection plan is updated for the remaining uncovered areas. The final reconstructed map of the gas distribution is computed using all the collected measurements, and gas source locations are estimated in the estimated GDM.

![Block diagram of our one-tour mission strategy 1t-ARME](image)
Algorithm 1 1t-ARMEx

1. Find $\pi_{gd}$ for the desired coverage ($\Omega$) of the target area;
2. $\mathcal{H} = \emptyset$;
3. while $\pi_{gd}$ is not empty do
4. Execute $c_1 \in \pi_{gd}$;
5. Update $(\pi_{gd} - c_1) \rightarrow \pi_{gd}$;
6. if high concentration is detected then
7. Estimate all $\mathcal{H}'$;
8. if $(\mathcal{H}' - \mathcal{H}) \neq \emptyset$ then
9. Find $\pi_{gdm}(\mathcal{H}' - \mathcal{H})$;
10. while $\pi_{gdm}$ is not empty do
11. Execute $c_1 \in \pi_{gdm}$;
12. Update $(\pi_{gdm} - c_1) \rightarrow \pi_{gdm}$;
13. Estimate all $\mathcal{H}'$;
14. if $(\mathcal{H}' - \mathcal{H}) \neq \emptyset$ then
15. Find $\pi_{gdm}(\mathcal{H}' - \mathcal{H})$;
16. Update $(\mathcal{H}' \cup \mathcal{H}) \rightarrow \mathcal{H}'$;
17. end if
18. end while
19. Update $(\mathcal{H}' \cup \mathcal{H}) \rightarrow \mathcal{H}$;
20. Find $\pi_{gd}$ for the remaining uncovered area;
21. end if
22. end if
23. end while
24. Build a GDM using all the measurements;

considering the current robot pose as a starting pose. The existing gas detection plan is required to be updated in order not to re-explore the area that is already covered by previously executed configurations, either for gas detection or gas mapping. In this way, the one-tour strategy plans and collect measurements using an adaptive replanning technique. Figure 19 shows a block diagram of the 1t-ARMEx.

4.3.1. One-tour inspection mission strategy. The overall procedure of 1t-ARMEx is summarized in Algorithm 1. It starts with creating a gas detection measurement plan for the desired sensing coverage $\Omega = [0, 1]$ of the target area, where $\Omega$ is a free parameter and indicates the fraction of full sensing coverage required. To maximize the likelihood of detecting all gas sources present, we can set the desired sensing coverage to $\Omega = 1$, and our sensor planning algorithm (Arain et al., 2015a,b) guarantees that all the cells are covered. However, in practice, some of the configurations are often very similar, heavily overlapping, and are selected only to cover a few cells that are not in the intersection of their coverage. This can happen due to, for example, either a narrow space that can only be covered by a specific sequence of largely overlapping sensor placements or a small area of the environment that is left to be covered after performing gas distribution mapping during the inspection.

In situations where the speed of execution is very important, setting the value of $\Omega$ to values slightly lower than 1 may allow the inspection mission to be completed with a significantly lower operational cost at only a small risk of missing a gas source. We conducted a simulation evaluation in our experimental environment map for $\Omega = [0.95, 1.00]$ with a step size of 0.01. The average results of seven experiments with different gas source layouts are shown in Figure 20. The required number of sensing configurations for $\Omega = 1$ (30.9 configurations) was reduced to 60.5% (18.7 configurations) for $\Omega = 0.95$. Similarly, the traveling distance was reduced to 89.6% (from 340.1 to 304.6 m) (10.4%).

The risk of missing a gas source is proportional to $(1 - \Omega)$ if it is assumed that gas sources are equally distributed among all unoccupied grid cells of the environment, and any gas source is confined to one grid cell only. However, in practice, the risk can be considered lower because: (1) in our approach, only the configurations that are heavily overlapping to the other configurations are discarded, which means that at the end of the mission, the uncovered cells are spread out all over the map, not just one big part of the environment; and (2) in real-world situations, gas sources are typically not confined to one grid cell only because we are dealing with gas plumes. Moreover, the relaxation of the requirement for sensing coverage applies to the planning of gas detection only. In the process of detailed gas tomographic reconstruction, 1t-ARMEx continues collecting gas measurements about detected hotspots that can add sensing coverage. Thus, the risk of missing a gas source is further reduced. As, for every detected hotspot, detailed gas tomography is carried out in the same way, the reconstruction quality of the final GDM depends only on the detection of gas sources. Therefore, the map quality will not be linearly affected by a growing risk of missing a gas source.

The gas detection plan for $\Omega < 1$ is computed in two steps. In the first step, the problem of full sensing coverage
measurement plan is not necessarily completely executed. Any gas detection event during the plan execution can trigger an interruption to update the plan for detailed gas tomography. Thus, often only a part of the TSP tour is actually executed, which can be sub-optimal as TSP can select two successive configurations far apart from each other to minimize the total traveling distance. Therefore, instead of solving a TSP, we sort the configurations so that always the closest configuration is chosen next, starting with the current position of the robot.

The main loop of the algorithm is to update and execute the measurement plans based on the magnitude of detected integral concentration and the estimated hotspots. Line 4 in Algorithm 1 is to execute the first configuration in $\pi_{gd}$ and update the list by removing the executed configuration. If a high integral concentration (500 ppm·m in our experiments) is detected, the measurement plan for gas distribution mapping will be computed for the estimated hotspots $\mathcal{H}^c$ (lines 7–21). While executing the current plan, if any new hotspots $\mathcal{H}^c$ are detected, the plan is updated accordingly (lines 11–15). Upon completion of measurement collection for gas distribution mapping in an area, the gas detection plan for the remaining uncovered area is computed (line 20) and executed. In the end, all the collected measurements are used to build a GDM of the environment. The GDM can be used to estimate the gas source locations.

5. Experimental evaluation

We designed an experimental setup to address the second research question by comparing the autonomy of ARMEx with the strategies of human experts teleoperating the robot for gas inspection missions. Our system concept is detailed in Section 3, and measurement planning for autonomous operations is described in Section 4. In this section, we report experiments that we conducted as a proof of concept and to compare the proposed autonomous strategies against teleoperated missions.

5.1. Robotic platform

Our prototype implementation of ARMEx, which we also used in the experimental evaluation, is shown in Figure 4. The robot moves with a maximum speed of 0.25 m/s. The RMLD sensor is mounted on a PTU 0.9 m above the ground level. For a sensing configuration, we set out the field of view $(\phi, r)$ as $(270^\circ, 15 \text{ m})$. The actuacted RMLD takes 100 s to sweep the field of view.

5.2. Environment and geometric map

We conducted experiments in a large indoor environment of about $120 \times 30 \text{ m}^2$ (Figure 22). To deploy the robot for an inspection task, we need access to geometric maps of the environment for path planning, robot localization, estimation of beam lengths, and measurement planning. The teleoperated robotic tour was conducted to build a 2D OGM and a 3D NDT map. The 2D OGM was used by the ROS navigation stack (Marder-Eppstein et al., 2010) for path planning, and the 3D NDT map was used with the NDT-MCL algorithm (Saarinen et al., 2013) for robot localization. The 2D OGM was translated into a binary grid for the estimation of beam lengths, and further downsampled into a 0.5 m cell size grid map for measurement planning. The unoccupied cells of the downsampled grid map needed to be observed for gas and were partitioned into reachable and unreachable, based on the robot length of about 1 m. Sensor placements were not permitted for the unreachable cells close to the boundary walls.

5.3. Gas sources

The ARMEx is designed for ground-level gas inspection and uses gas tomography to model gas distributions, which may stem from contained gas sources or more complex gas plumes of freely escaping gas. For the evaluation of the proposed system, we need methane sources that can be detected. As we cannot release methane indoors owing to safety restrictions, we used standard 2-liter transparent plastic bottles filled with methane as a gas source in our
experiments. The RMLD beam can pass through the bottles and can read the gas concentrations inside the containers. A shortcoming of using gas bottles is that they confine the gas in a container and prevent its free discharge in the environment. This simplifies reconstruction through gas tomography (which is not the focus of this article) but makes gas source detection and localization more challenging because gas is contained in small volumes. A noteworthy advantage of using gas in bottles is that accurate ground-truth information about the gas distribution is available for system evaluation.

A gas column of about 1 m height and 0.1 m width was built using three bottles (Figure 21). In the experiments, 25 gas columns were used to construct 8 different gas sources: 3 columns in each of the 7 gas sources and 4 columns in one of the gas sources.

5.4. Experimental runs

We performed six experiments by placing gas sources at different locations in the environment. In each of the experiments, an autonomous mission was completed using our two mission strategies: (1) two-tour strategy in which gas detection and gas distribution mapping tasks are performed in two subsequent robotic tours, which we refer to as 2t-ARMEx; and (2) one-tour adaptive strategy that performs both tasks in a single robotic tour, referred to as 1t-ARMEx. In addition to autonomous gas inspection, strategies of human experts (h-expert) were also carried out. A user interface was designed for the experts to decide on the next measurement location after each map update.

Four experts performed six experiments: two of them performed two experiments each, and two performed one experiment each. It is very difficult to carry out these experiments with a sufficiently large representation of human operators. We rather chose a highly biased group of participants who are expected to fare best on the inspection tasks. The selected human experts have a research background in the field of mobile robot olfaction. They were familiar with the mapping algorithm, the sensing principle, and even the adaptive sensor planning methods described in this article before they carried out the experiment. The results of the human experts are thus supposed to give an idea of the best performance that human operators are capable of.

5.5. User interface for human experts

The human experts were provided with a remote control station with a user interface to decide where the robot should perform measurements, see Figure 23. The interface displays the robot model localized in the environment map, including the actuated remote gas sensor. The expert can interactively select a goal pose for the desired sensing configuration based on the intermediate reconstruction map computed using all measurements collected so far. The sampling process is visualized by displaying the optical beams in the circular sector of the field of view. This cycle continues until the expert decides to terminate the gas inspection mission.

In the experiments, the experts were provided with no prior information about the placement of gas sources. There was no camera picture available for the operators, the displayed maps on the interface was the only information to locate the gas sources. The control station connected through a wireless network was located outside the monitoring area to prevent the user from seeing the actual location of the gas columns.

5.6. Quantitative evaluation

All the mission strategies were evaluated quantitatively, using the following criteria: (1) the number of sensing configurations; (2) the total distance traveled by the robot; (3) the total sensing coverage; and (4) the reconstruction quality of the generated GDMs. The first two quantitative criteria are about the solution costs and the last two are about the generated solution quality.

5.6.1. Solution costs. The results for the first two criteria are shown in Figure 24. For the number of sensing
configurations (Figure 24(a)), the one-tour strategy provided the most economical solutions. It used the least sensing configurations in five out of six experiments, and only in one experiment did it consume one configuration more than human experts. As expected, the two-tour strategy was the most expensive owing to executing independent robotic

Fig. 22. The experimental environment. The central column shows the environmental map, and the left and the right columns show views from different environment locations. A 0.5 m cell size Cartesian grid map is placed over the OGM. The area under the green and blue cells of the Cartesian map is for the gas inspection. The green cells are reachable by the robot and are considered as candidates for sensor placement. The blue cells are not reachable by the robot owing to its size and, therefore, are not permitted for sensor placement. Three particularly interesting areas are marked with rectangles and corresponding solutions are shown in Figure 29.
tours for gas detection and gas distribution mapping. The human experts used more configurations than the one-tour strategy to complete the inspection mission in three experiments. The average results of all the six experiments are summarized in Table 2, which indicates that, on average, the number of configurations selected by the two-tour strategy and human experts was 16.3 and 2.7 higher than the one-tour strategy. Thus, our one-tour adaptive mission

Fig. 23. The user interface designed for operators to conduct the monitoring task. A snapshot taken during an experiment performed by one of the experts is shown. In the environment map, the sampling process started from the right side and progressed toward the left. Displayed are: (a) the robot poses of the executed configurations as gray arrows; (b) the path followed by the robot between the configurations as a gray line; (c) the reconstructed GDM as yellow-to-red bubbles of low-to-high concentrations; (d) the expert’s decided pose for the current configuration as a red arrow; (e) the circular sector of the configuration being executed in blue, and an optical beam indicated with a red line. In addition to the snapshot shown, event-based messages are also displayed for the user, e.g., when the gas map is updated.

Table 2. Quantitative comparison between the one-tour strategy (1t-ARMEx), two-tour strategy (2t-ARMEx), and strategies of human experts (h-expert). The results are shown as average ± standard deviation.

| Performance measure         | 1t-ARMEx   | 2t-ARMEx   | h-expert   |
|-----------------------------|------------|------------|------------|
| Operational cost:           |            |            |            |
| - Sensing configurations    | 18.00±2.53 | 34.33±1.75 | 20.67±1.75 |
| - Traveling distance (m)    | 303.21±30.98 | 512.58±8.04 | 266.95±12.13 |
| - Operational time (s)      | 3787±379   | 5483±186   | 3134±186 * |
| Sensing coverage            | 0.97±0.01  | 1.00±0.00  | 0.95±0.03  |
| Reconstruction quality:     |            |            |            |
| - True positives (target value: 8) | 7.50±0.55 | 7.17±0.75 | 7.17±0.75 |
| - False positives (target value: 0) | 5.33±0.82 | 5.33±2.42 | 6.83±2.62 |
| - Recall (target value: 1)  | 0.94±0.07  | 0.90±0.09  | 0.90±0.09  |
| - Precision (target value: 1) | 0.59±0.04 | 0.59±0.11 | 0.53±0.11  |
| - F1 score (target value: 1) | 0.72±0.05 | 0.71±0.09 | 0.66±0.11  |

*The operational time for the human experts is computed without taking into account the analysis time to decide the next sensing configuration by looking at the previous measurement poses and the updated gas map.
strategy outperformed the two-tour and the human expert strategies in terms of solution cost for the number of sensing configurations.

For the solution cost of traveling distance (Figure 24(b)), the two-tour was the most expensive strategy as, on average, the robot had to travel 512 m to visit the selected configurations for an experiment, compared with 303 m for the one-tour and 267 m for human experts. The two-tour was that expensive owing to the same reason as mentioned for the number of sensing configurations, i.e., two robotic tours are to be executed instead of one for the other two strategies. However, for the traveling distance, the one-tour strategy was slightly more expensive than the strategies of human experts.

The operational time for the autonomous strategies can be computed from the above information of the total number of selected configurations and 100 s sensing time of each configuration, and the total path distance traveled by the robot and a maximum speed of 0.25 m/s, as described earlier in Section 5.1. For the one-tour strategy, 18 selected configurations cost 1,800 s for sensing, and 303.21 m of path distance cost approximately 1,213 s for traveling. The average computation time to replan gas mapping each time a new hotspot is detected or for gas detection after an accurate gas tomography is performed in the area is approximately 774 s. This results in an average operation time of 3,787 s (about 1 hour and 3 minutes). Similarly, the average operational time for 2t-ARMEx is 5,483 s (about 1 hour and 31 minutes, without considering any computation time as the robotic tours for gas detection and gas distribution mapping are computed before executing the plan). The average operational time for human experts without considering the time required to analyze and deciding the next configuration in each step is approximately 3,134 s (about 52 minutes). We do not assume a number for the analysis time of human experts.

For a simplistic theoretical comparison with an in situ sensor, we assume a Roomba-like robot that has to visit each grid cell of the map without any requirement of necessary pause to collect gas samples (in reality an in situ sensor would require tens of seconds for response and recovery time, for example, a metal-oxide sensor). We computed the total path distance of 3,212 m by solving a TSP. This would require about 12,848 s (about 3 hours and 34 minutes) of operational time. Thus, a gas inspection performed with remote gas sensing using the one-tour strategy is about three times as fast and using the two-tour strategy is about twice as fast as in situ sensing.

5.6.2. Solution quality. For the solution quality of total sensing coverage (Figure 25), the gas detection tours of the two-tour strategy were planned for 100% sensing coverage. The minimum desired coverage for the one-tour strategy was set...
to 95%, and the human experts were not explicitly instructed to cover the whole area, but to create an accurate gas map to locate the gas sources. On average, the sensing coverage provided by one-tour, two-tour, and human expert was 97%, 100%, and 95% of full coverage. It is worth noting that the one-tour strategy selects the least configurations and provides higher sensing coverage than the strategy of human experts. Thus, it can be concluded that the one-tour strategy selects better sensor placement than that of human experts.

The reconstruction quality of different experimental runs is evaluated on account of a comparison between the estimated gas sources from the maps and the true gas sources placed in the field. In freely escaping gas, the highest concentrations are not always at the source locations, for example, due to accumulation effects. In that case, the variance map of gas distributions often provides better estimates of the source locations (Hernandez Bennetts et al., 2014). In this article, we use mean GDMs owing to contained gas sources. The variance map does not produce much information because only a small variance can be expected around the sources, compared with high mean concentrations at the source locations. Therefore, we use the mean gas maps with the estimated hotspots at the high-concentration peaks to source locations.

The gas sources are estimated in a similar fashion as the hotspots in Section 4. Among the estimated gas sources, we find true positives that correctly indicate gas sources and false positives that incorrectly indicate gas sources. The gas tomography reconstruction could well result in multiple gas patches around the source locations. We consider all the estimated peaks within 3 m obstacle-free distance as a true positive, and the rest of the estimations are false positives. Figure 26(a) shows one of the reconstruction maps with true and false positives as well as the locations of true gas sources.

To measure the performances of different strategies for the estimation of gas sources, precision and recall are computed. Precision is the proportion of true positives of gas sources among true and false positives, and recall is the proportion of true positives among all the gas sources (Lewis, 1991). To combine both measures, we used the F1 score (Chinchor, 1992).

Figure 27 shows the number of true and false positives, precision, recall, and the F1 score for all the experiments, and the average results along with standard deviation are provided in Table 2. The target values in Figure 27 are: 8 in Figure 27(a), 0 in Figure 27(b), and 1 in Figure 27(c)-(e). The one-tour adaptive strategy has consistently performed better than the other strategies as it has the smallest standard deviation and the highest F1 score.

5.7. Shortcomings and limitations

It should be noted that in all the experiments, the gas sources are estimated with a high number of false positives.
This happened since the resultant GDMs contained disjoint high-concentration patches around the gas sources. These misclassifications are the result of different issues that can occur at the same time: (1) robot localization errors; (2) an inaccurate calculation of the length of the sensor beams; (3) imprecisions in the reconstruction algorithm; (4) non-uniform gas distributions in the gas columns can lead to inaccurate reconstructions when the optical beam is hitting neck of the bottle; (5) faulty readings because the beams are not properly reflected owing to the shape and material of the reflective surface; (6) waste bins located in the field sometimes also report gas concentration. The first three issues are system-related problems, and the last three occur owing to the realistic experimental conditions.
Projected optical beams to collect integral measurements can lead to a false positive when localizing the gas source. The reconstruction algorithm (Hernandez Bennetts et al., 2014) has closely decomposed the integral measurements among the grid cells covered by the sensing configurations. However, the algorithm has estimated a high concentration in a cell on the edge of the field of view, crossed by a single, short beam segment. This can lead to a false positive when localizing the gas source.

Robot localization errors propagate into inaccurate localization of the projected beams, and thus the resultant reconstruction quality is compromised. As the remote gas sensor can report only the integral concentration and cannot estimate the beam length, we compute the beam length by using the sensor pose and casting a ray on a 0.05 m cell size geometric map of the environment. However, even small localization errors can introduce high inaccuracies in the computation of beam lengths, especially when they are close to edges or non-perpendicular surfaces. In some of the areas, localization error of more than a meter was noted, although this was only a few times.

Moreover, the 2D geometric map used to compute the beam length is an approximate representation of the environment. When creating the OGM, the occupied space in 2 m height is directly projected to the ground. As the experiment environment contains stairs and plants, an optical beam can reach a gas source that is occluded on the map. This will result in an inaccurate estimation of the beam length.

Another system-related issue was the reconstruction algorithm itself. The algorithm is formulated as least-square optimization that decomposes the integral gas measurements into a grid map. Grid cells on the edge of the field of view of a sensing configuration that are crossed by a single, short beam segment might generate a high-concentration estimate that counts a false positive, see Figure 28.

To verify that the real-world issues mentioned previously have a significant influence on the results, we conducted simulation experiments in the same environment using the same layouts of gas sources. In the simulation, all gas sources were correctly located with zero false positives. The estimated gas sources in a simulation experiment corresponding to the real-world experiment in Figure 26(a) is shown in Figure 26(b).

In our experiments, the proposed system is not evaluated with freely discharging gas. We use a tomographic reconstruction algorithm (Hernandez Bennetts et al., 2014) that aims to capture the statistical properties of gas distributions. The least-squares algorithm decomposes the collected integral measurements by estimating the mean and variance of the gas distribution in a grid. The measurements for the algorithm are assumed to be generated by a stationary random process. As long as this assumption holds and there are sufficiently many informative samples available, this process should be captured by the reconstruction algorithm. In our previous work, we have demonstrated gas distribution mapping with our gas tomography algorithm with contained methane sources (Arain et al., 2016) as well as freely discharging methane sources (Hernandez Bennetts et al., 2014). As long as the reconstruction algorithm can capture gas distributions of freely discharging gas, the sensor planning will also work. Other than for safety reasons, we chose contained gas sources for our evaluation in order to have ground-truth information to evaluate the map quality. We chose a complex indoor environment instead of an outdoor area because it poses more challenges to select suitable sampling configurations if the robot cannot just go to the optimal configurations like in an open environment.

5.8 Qualitative evaluation

Now we assess the selected configurations qualitatively. As the sensor placement for gas distribution mapping depends upon the estimated hotspots, the two-tour strategy has a distinct advantage of using prior global information in the form of a coarse gas map, created after the full sensing coverage is provided. Thus, hotspot estimates tend to be better, especially in a static environment where the confined gas sources are placed at fixed locations. In contrast, the one-tour strategy can use only local coarse maps to compute measurement plans for gas distribution mapping. These coarse maps are created after each step during the inspection. However, the one-tour strategy (and also human experts) can adopt changes in the environment as the next sensing configuration is selected based on the previous reconstructions.

The human experts found it difficult to select optimal sensing configurations, as, in general, they seem to look for less-complex paths and did not find some sophisticated sensor placements that could have provided better coverage. On the other hand, configurations selected by the one-tour strategy provide better cross angles and sensing coverage, which are the key factors in the reconstruction quality.

Among the experts, the balance between exploration and exploitation was one of the main differences. For example, two experts used 20 configurations in 2 different experiments, resulting in a sensing coverage of 0.97 and 0.93, to successfully localize 6 and 8 gas sources. This means, Expert 1(a) explored more areas for gas detection, and Expert 2(a) better mapped the high-concentration areas to locate the gas sources. In the other two experiments, Expert 1(b) used 18 and Expert 2(b) used 23 configurations for nearly the same sensing coverage. They localized
7 and 8 gas sources, which means Expert 2(b) used 5 additional configurations for gas mapping. The experts who did two experiments utilized 1 and 2 fewer configurations in their second experiments; however, the reconstruction quality for Expert 1(c) was improved, and for Expert 2(c) it was decreased. They did their second experiment without the evaluation of their first experiment.

A comparison of the solution quality in the highlighted areas in Figure 22 is shown in Figure 29. Figure 29(a) and (b) is an example where the expert places a relatively high number of configurations, and Figure 29(c) and (d) is an example where the plan of the human expert does not have sufficient overlapping sensing coverage. This comparison indicates that it is difficult for a human to be consistent and decide the optimal sensor placement based on multiple factors. In another case, when the robot was placed close to an obstacle, and a gas source was detected between the robot and the obstacle, the human expert decided only a single sensor placement and did not choose an unnecessary additional configuration to obtain nearly the same reconstruction quality. On the other hand, the one-tour strategy selected two configurations (Figure 29(e) and (f)).

To summarize the quantitative and qualitative assessments, the one-tour strategy proposed in this article provides the best reconstruction quality with the lowest variance and uses the fewest configurations. Common feedback from the experts who performed the experiments is that deciding an optimal sensor placement for a human is difficult. For example, it is hard to decide a measurement pose while looking at the current gas map, the previous measurement poses, and estimating the area that can be covered. We make autonomous gas inspection possible with a few assumptions: (1) geometric map of the environment is available; (2) measurements are collected at discrete poses; (3) the inspection environment is a nearly flat surface; and (4) there is enough time to carry out the gas sampling. Our autonomous measurement strategies are strong contributions to sample the environment efficiently and accurately with a remote gas-sensing mobile robot, which was not possible previously. Moreover, enabling autonomous gas detection and gas distribution mapping means that many hazardous applications can now be considered that otherwise would require humans to be in dangerous areas, such as disaster situations.

Fig. 29. Comparison of sensor placement decided by human experts (h-expert) and one-tour strategy (1t-ARMEx). The poses of the selected sensor configurations are shown with blue arrows. The gas sources are indicated with purple dots (one dot is one gas column), and the reconstruction of the gas distribution is shown in yellow-to-red for low-to-high concentration. (a), (b) The human expert used four additional configurations compared with the one-tour strategy while also estimating two gas sources. (c), (d) The sensing configurations selected by the human expert do not provide sufficient sensing overlaps of desired cross angles. (e), (f) Only one configuration is used by the human expert to localize a gas source placed in a small space between the robot and obstacles. The one-tour strategy selected two configurations.
6. Conclusions

Greenhouse gas emissions are a major cause of global warming, and vigilant monitoring is required to locate high-concentration areas and analyze fugitive emissions. A remote gas sensor carried by a mobile robot provides the possibility for adaptive gas inspection in large environments. We propose an Autonomous Remote Methane Explorer (ARMEx): a mobile robot-based actuated remote gas sampling system capable of searching for and localizing gas sources in an efficient manner. In our work, we have designed measurement planning techniques to perform autonomous gas inspection missions.

The major contributions of this article are as follows.

1. We have presented an autonomous robotic solution for gas inspection missions with an actuated remote gas sensor. We have developed sensor planning algorithms that aim at optimizing performance criteria for gas detection and gas distribution mapping while minimizing the number of measurements and the total traveling distance.

2. In a layer above the sensor planning algorithms, we have designed a mission strategy to efficiently sample the environment for combined inspection tasks of gas detection and gas distribution mapping. Our one-tour adaptive strategy (1t-ARMEx) interleaves the initially planned exploration for gas detection each time a high concentration is detected with a detailed tomographic reconstruction. After that, the gas detection plan is updated for the remaining uncovered area. In this way, it provides an adaptive solution that outperforms our previous approach of performing gas detection and gas distribution mapping in subsequent robotic tours (2t-ARMEx).

3. We have validated and compared our autonomous measurement planning strategies in real-world experiments against human experts teleoperating the robot. The experimental results show that the autonomous system consistently produced better gas maps, and our new 1t-ARMEx strategy performed these missions with the least number of sensing configurations.

4. We bring gas-sensing robots to relatively large environments. The major limiting factors for large-scale operations are the range of gas sensors and to find optimal sensing configurations in large search spaces. We use a remote gas sensor and design efficient sensor planning algorithms that quickly find near-optimal solutions.

We believe that this work is a major step to bring mobile robot olfaction systems into practical applications in large environments. Our proposed system can further be improved to increase its reliability. In remote gas sensing, accurate robot localization is important because, in addition to the incorrect estimation of the sensor pose itself, the localization error can further propagate in the beam length calculation and, consequently, in the decomposition of integral measurements. Uncertainties in the robot pose can be considered in the process of gas mapping (Lilienthal et al., 2007) to overcome the effects of the localization error.

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Notes

1. See https://www.clearpathrobotics.com
2. See https://www.sewerin.com
3. See https://schunk.com
4. See https://www.sick.com
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