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Gasbot: A mobile robotic platform for methane leak detection and emission monitoring

Victor Hernandez Bennetts*, Achim J. Lilienthal[†], Ali Abdul Khaliq[†], Víctor Pomareda Sesé[‡] and Marco Trincavelli[†]
*AASS Research Centre. Örebro University. SE-70182. Örebro, Sweden.

Email: victor.hernandez@oru.se

†AASS Research Centre. Örebro University. SE-70182. Örebro, Sweden.

‡Institute for Bioengineering of Catalonia (IBEC). 08028. Barcelona. Spain.

Abstract—Due to its environmental, economical and safety implications, methane leak detection is a crucial task to address in the biogas production industry. In this paper, we introduce Gasbot, a robotic platform that aims to automatize methane emission monitoring in landfills and biogas production sites. The distinctive characteristic of the Gasbot platform is the use of a Tunable Laser Absorption Spectroscopy (TDLAS) sensor, along with a novel gas distribution algorithm to generate methane concentration maps of indoor and outdoor exploration areas. The Gasbot platform has been tested in two different scenarios: an underground corridor, where a pipeline leak was simulated and in a decommissioned landfill site, where an artificial methane emission source was introduced.

I. Introduction

Leak detection and emission monitoring in biogas facilities, more specifically landfill sites, are of critical importance and are gaining particular interest among EU authorities [1]. Landfill emissions account for 2% of the total Green House Gases (GHG) released by human activity [2]. GHG are mostly composed by methane (CH_4) and carbon dioxide (CO_2) . In addition to GHG, poisonous gases like hydrogen sulphide (H_2S) can be released from biogas production sites. A landfill operator is required to issue monthly reports of methane emissions and usually, methane measurements are taken manually at a few predefined locations (such as bore holes or at the borders of the landfill). This spatial and temporal sparsity in the measurements complicates the detection of leaks and ultimately, it causes a waste of resources and in a substantial emission of GHG.

Landfill monitoring with static grids of sensors has been proposed as a solution. In [3], the authors developed a sensor module able to monitor methane and send reports to a central station. The authors validated their system by placing several sensor modules near the bode wells of a landfill site. While this approach copes with the temporal sparsity, the measurements are still restricted to a few specific locations, which need to be determined during deployment.

Mobile robotics can contribute to mitigate the spatial sparsity of the measurement by providing a versatile system that is able to adaptively collect measurement at different locations on a landfill site. Mobile robots can outperform human operators since, they are able to conduct repetitive measurements without suffering from fatigue and they can be exposed to hazardous conditions, for example areas with high H_2S concentrations [4].

Additional challenges arise due the limitation of current sensing technologies. Traditional sensors (such as metal oxide sensors) require a physical interaction between its sensitive layer and the gaseous substance. This means that the sensor has to be moved to the area of interest in order to collect measurements that cover a few centimetres. In addition, metal oxide sensors are partially selective. For real world applications, the presence of more than one type of gaseous compound should be taken in consideration [5]. Alternative sensing technologies emerged in the 90's when TDLAS devices became available. A TDLAS sensor can remotely measure concentration of gases and, by tuning its emitting beam, a TDLAS sensor can become highly selective to a specific gas, for example methane [6]. Instead of reporting point measurements, TDLAS devices report concentration values as an integral measurement over the path of the laser beam.

The working principle behind TDLAS sensors is that, gas molecules absorb energy in narrow bands of the electromagnetic spectrum around specific wavelengths. Outside these bands, there is no absorption. TDLAS sensors emit laser beams tuned at the absorption band of the target gas. The laser diodes are modulated in a way that, the emitted beam is driven on and off of the wavelength of interest. During this process, the power of the beam is measured continuously and, by comparing the measurements when the beam is on the target wavelength against the measurements when the beam is off, it is possible to determine, with high degree of selectivity, whether the emitted beam has traversed a concentration patch or not.

Previous works have attempted to detect CH_4 using TDLAS sensors. In [6], a TDLAS sensor was mounted on a car and on an air plane in order to demonstrate the feasibility of using TDLAS sensors for identifying areas with CH_4 concentration. However, no further processing of the integral concentrations was proposed. In [7], the authors proposed the use of a TDLAS sensor, mounted on a pan-tilt unit, and an array of reflective surfaces to estimate the CH_4 concentrations from an agricultural site. The focus of this work was in the estimation of the total amount of emitted CH_4 per unit of time. Using an Optical Methane Detector (OMD), Grinham et

al. [8] proposed a system to improve the quantification of CH_4 released rates from a water storage site. The authors mounted a single-path OMD to an autonomous vessel in order to collect CH_4 measurements over a prolonged period of time. The data collected by the robotic vessel allowed the authors to identify areas of high CH_4 ebullition as well as to estimate release rates.

In this paper, we present Gasbot, a robotic platform aimed at the landfill monitoring tasks. The Gasbot platform is equipped with a TDLAS sensor and, by combining different sensing modalities, it creates CH_4 distribution maps of a given exploration area using a novel gas distribution modelling algorithm. The Gasbot project is being funded by Robotdalen¹ and it is currently under development in cooperation between the Örebro University and Atleverket AB^2 , the agency in charge of waste management and biogas production in the province of Örebro, Sweden.

The remainder of this paper is structured as follows: Section II describes the components of the Gasbot platform. In Section III, we explain the algorithm to generate gas distribution maps from integral concentration measurements. In Section IV, the testing scenarios are described. Results are presented in Section V, followed by conclusions and suggestions for future work in Section VI.

II. THE GASBOT PLATFORM

The prototype version of the Gasbot platform is shown in Figure 1. It comprises an ATRV-JR all terrain wheeled robot equipped with a pan-tilt unit (PTU-D46-70), two laser scanners of the same model (LMS200), a TDLAS sensor (Sewerin's RMLD) and a GPS unit (MTi-G). All sensors and software modules work under the Robot Operating System (ROS) [9].

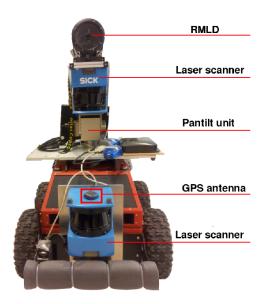


Fig. 1. Gasbot robotic platform

To sense CH_4 concentrations, the robotic platform was equipped with a Remote Methane Leak Detector (RMLD) manufactured by Sewerin. The RMLD belongs to the family of TDLAS sensors which, compared to traditional gas sensing mechanisms, do not require a direct interaction between the sensor's surface and the target compound. Instead, gas sensing is performed remotely and concentrations are reported as integral measurements (in $ppm \cdot m$). According to the manufacturer's data sheets, the RMLD is able to measure CH_4 in concentrations as low as 5 $ppm \cdot m$ at distances up to 15 m, and 10 ppm \cdot m at distances up to 30 m. The upper detection limit of the RMLD is 99999 $ppm \cdot m$ [10]. In comparison, a calibrated TGS2611 metal oxide (MOX) sensor from Figaro engineering can measure CH_4 concentrations in a range between 500 ppm and 10000 ppm [11]. Figure 2 exemplifies the measurement principle of the RMLD where, an operator aims a 500 ppm CH_4 patch.

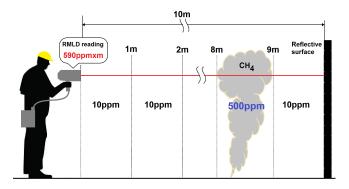


Fig. 2. Measurement principle of the RMLD. In this example, the device reports an integral concentration measurement of $590 \ ppm \cdot m$ when the infrared beams travels a $10 \ m$ path in which, a background concentration level of $10 \ ppm$ and a CH_4 patch of $500 \ ppm$ are present.

An sensor unit comprising a Pan-Tilt Unit (PTU), the RMLD and a laser scanner, allows the Gasbot platform to create CH_4 measurement scans of the exploration area. Gasbot is equipped with a PTU-D46-70, which is a PTU that can support payloads up to $4.06 \ kg$ with pan and tilt ranges of $(78^{\circ}, 180^{\circ})$ at a 0.003° resolution. On top of the PTU, a laser scanner SICK LM200 is mounted along with the RMLD. The purpose of the laser scanner mounted on top of the PTU is to collect range information that allows to create three dimensional representations of the exploration scene. Inside these scene models it is possible to project the RMLD rays and thus estimate their starting and ending points inside the robot's coordinate frame. These coordinate points are used by the gas distribution mapping algorithm as later explained in Section III. The 3-D scene models were created using Octomap [12], which is a probabilistic 3-D modelling library implemented in ROS.

While the ATRV-JR has encoders to provide odometry readings, one typical problem with odometry localization is that errors in position quickly accumulate over time [13]. This is particularly critical in scenarios where the robot is expected to explore large areas. A common solution to improve

¹ http://www.robotdalen.se/en/

²http://www.orebro.se/3611.html

the localization performance is to fuse sensing modalities, along with the robot's odometry readings. Indoor and outdoor localization was performed separately using different sensing modalities fused with the robot's odometry information. For outdoor localization, a MTi-G sensor is used. The MTi-G is a GPS-aided Inertial Measurement Unit (IMU) manufactured by Xsens [14]. In indoors, a second LMS200 laser scanner was mounted near the frontal bumper of the robot, which provides 2D scans with a field of view of 180° at a resolution of 1° to a range up to 80~m.

Laser scans and odometry were fused using AMCL, which is a ROS package that implements an adaptive Montecarlo localization algorithm [15]. AMCL tracks the robot's pose inside a known grid map using a particle cloud filter.

The absence of natural landmarks and the uneven terrain conditions in outdoor scenarios, such as a landfill site, prevents the use of a Montecarlo localization approach. Instead, we opted for the MTi-G module to localize the robot. A limitation of this device is that, as the velocity of the robot decreases, the output position increasingly drifts. Therefore we implemented an ad-hoc solution to filter the GPS position and orientation readings. The position (x_t, y_t) at time t is iteratively computed as:

$$x_t = x_{t-1} + \omega \cdot \Delta_x^{GPS} + (1 - \omega) \cdot \Delta_x^{odom}$$
 (1a)

$$y_t = y_{t-1} + \omega \cdot \Delta_y^{GPS} + (1 - \omega) \cdot \Delta_y^{odom},$$
 (1b)

where (x_{t-1},y_{t-1}) are the filtered coordinates at the previous iteration and ω is a weighting function that depends on the robot's velocity. In a systematic way, we selected ω as a step function that switches between 0 and 1 when the robot's velocity is below a threshold of 0.15~m/s. This means that, when the velocity of the robot falls below the threshold, the filter will solely rely on the odometry readings to update the position estimate.

III. GAS DISTRIBUTION MAPPING ALGORITHM

As previously stated, TDLAS sensors report concentration values as integral measurements. Therefore, gas distribution algorithms that use point measurements as inputs [16], [17] are not a viable solution. We opted for a novel approach proposed in [18] by Trincavelli et al. where the problem of gas distribution modelling is framed as an optimization problem and the integral measurements from TDLAS sensors are used to update a grid model in an analogous way as in Computer Assisted Tomography, where body images are reconstructed from a set of attenuation measurements of e.g. X-rays.

The algorithm in [18] decomposes the integral concentration measurements y reported by a TDLAS as follows:

$$y = \sum_{i=1}^{M} l_i x_i + \epsilon, \tag{2}$$

where M is the number of cells traversed by the TDLAS beam, l_i is the distance travelled by the beam in cell i, x_i is the concentration in cell i and ϵ is the measurement

noise term. An example of the decomposition of the integral concentration measurements can be seen in Figure 3. The task of gas distribution mapping is then formulated as the problem of estimating the vector of concentrations ${\bf x}$ which best explains a set of N measurements. Thus, the measurement dataset becomes an $N\times M$ matrix described by the following equation:

$$\mathbf{y} = \mathbf{L}\mathbf{x} + \epsilon \mathbf{1}.\tag{3}$$

In the above equation, \mathbf{L} is an $N \times M$ matrix that contains the traversed distances for each measurement, \mathbf{x} is an M column vector that contains the concentration values for the traversed cells and $\mathbf{1}$ is a column vector of ones of length N. In order to compute the likelihood of the measurements, a Gaussian distribution is assumed for ϵ . This means that the noise in the TDLAS sensor is unbiased. In addition, a Gaussian prior distribution over \mathbf{x} is defined to limit the number of solutions. In this way, the gas distribution problem can be framed as the following optimization problem:

minimize
$$\|\mathbf{L}\mathbf{x} - \mathbf{y}\|_2 + \lambda \|\mathbf{x}\|_2$$
 (4) subject to $\mathbf{x} \succeq 0$,

where λ is a parameter that determines the strength of the prior and the constraint $\mathbf{x} \succeq 0$ is added to discard negative gas concentrations.

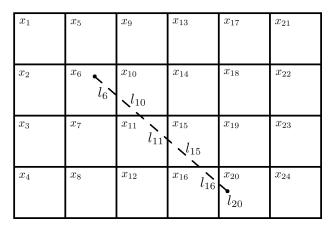


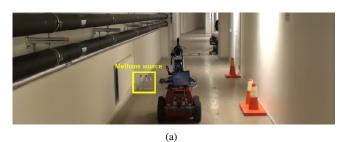
Fig. 3. Integral measurement decomposition. In this example, a TDLAS beam (denoted by a dashed line) travels inside a 4×6 lattice. The integral measurement is decomposed as $y=l_6\times x_6+l_{10}\times x_{10}+l_{11}\times x_{11}+l_{15}\times x_{15}+l_{16}\times x_{16}+l_{20}\times x_{20}+\epsilon$, where ϵ is the measurement noise.

IV. EXPERIMENTAL SCENARIOS

The Gasbot platform was tested both, indoors and outdoors locations. In the first scenario, the aim is to simulate an indoor facility where a transport pipe is leaking CH_4 . This scenario was simulated in an underground corridor (Figure 4(a)) located in Örebro University's main campus. Due to safety concerns, the leak was simulated by placing a set of sealed transparent flasks filled with natural gas (90% CH_4) on the floor. While this set-up does not capture the complexities of a gas leak, since the CH_4 is kept isolated from the testing environment inside the flasks, it allows nevertheless to

evaluate the gas distribution map by locating the area of high CH_4 concentration where the flasks are located. The Gasbot platform was commanded to autonomously patrol an area of $15\ m \times 2.5\ m$ following a pre-defined exploration path where data was collected at four different way-points

For the second scenario (Figure 4(b)), the Gasbot platform was deployed in Atleverket's decommissioned landfill in Rynningeviken, Örebro. An artificial, controlled CH_4 concentration was generated by releasing natural gas (90% CH_4) from a tube ring connected to a cylindrical container. The release rate was not recorded during the experiments. The robot was remotely operated to explore an area of $18\ m \times 11\ m$ and measurements were taken at three different locations. Please note that no reflectors need to be installed in the environment, since the TDLAS beam was reflected by either the ground or the walls.



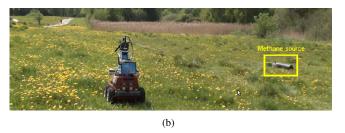


Fig. 4. Experimental scenarios. (a) Indoors. (b) Outdoors.

V. RESULTS

In figures 5(a) and 5(b) the generated gas distribution maps are shown. Since the cell size of the distribution maps was set to $1\ m$ and the RMLD was mounted slightly over $1\ m$ up from the ground, the distribution models are approximated as 2D structures by showing only one layer of the 3D map. In the figures, the yellow cylinders denote the actual location of the CH_4 source. The blue/red squares denote the position of the robot and the blue lines are the ray projections from the RMLD.

In the indoor experiment, the PTU was programmed to perform a sweeping movement from $(-17.76^{\circ}, 11.46^{\circ})$ in pan and $(-13.70^{\circ}, 0.15^{\circ})$ in tilt. The PTU stopped for 2~s at each of the 144 measurement points in the sweeping trajectory. In the outdoor scenario, the PTU panned from $(-60^{\circ}, 60^{\circ})$ and tilted $(-14^{\circ}, -3^{\circ})$. The PTU stopped for 1~s at each of the 240 measurement points in the sweeping trajectory. It can be noticed that, in both maps, high concentrations (denoted by darker shades) are predicted at locations near

the gas sources. In the underground experiment, the highest concentration cell matches the actual gas source position and cells with concentrations above $0\ ppm$ are predicted only near the gas source. This is an expected result since the CH_4 concentrations are enclosed inside the flasks and it is never let to evaporate thus, a plume is never formed.

At the landfill site, CH_4 is constantly released at uncontrolled rates. The interaction between the released CH_4 and the environment creates complex structures where turbulence can mender the plume while airflows can move the CH_4 patches away from the source. This is reflected in the generated gas distribution map of Figure 5(b), where it can be noticed that high concentration cells are spread all over the exploration area.

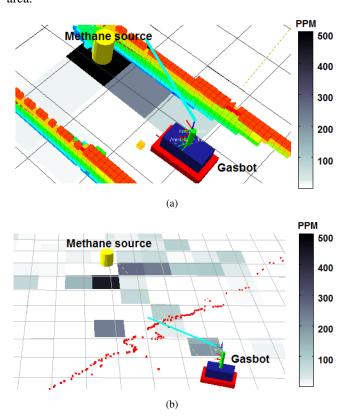


Fig. 5. Generated gas distribution maps. (a) Indoors. (b) Outdoors. The grid cell size was set to $1\ m$.

VI. CONCLUSIONS

In this paper we presented a mobile robotic platform for the monitoring and inspection of landfill areas. The Gasbot platform is equipped with a state-of-the art TDLAS sensor to monitor CH_4 concentrations. Since TDLAS sensors report integral instead of point measurements, a novel gas distribution modelling novel approach, analogous to CAT imaging was used.

The Gasbot platform was tested indoors and outdoors and, while no quantitative or ground truth evaluation was possible, the spatial distribution of the produced CH_4 concentration maps showed to be consistent with the actual location of

the gas sources. The results demonstrate that mobile robots can contribute to the task of landfill monitoring, not only by automating measurements, but also by providing gas distribution maps, that highlight areas where where high CH_4 concentrations can be found. This information can be useful to the landfill operator to detect CH_4 leaks.

Future work will aim to improve the localization of the robot in outdoor environments. The current implementation is more prone to errors than its indoors counterpart. Errors in localization translate in misalignments in the gas concentration predictions. The distribution modelling algorithm can be improved, e.g. by integrating the localization uncertainty in the computation of the gas distribution maps.

Integration of wind measurements in the computation of the gas distribution model is not straightforward using the current mapping algorithm. This is due to the measurement principle of the TDLAS, which returns integral concentration measurements of the path travelled by the sensor beams. In contrast, wind measurements with e.g. ultrasonic anemometers, provide point measurements of the wind conditions at the current location of the robot. However, wind information could be used for a sensor planning algorithm, to estimate plausible exploration paths for the task of CH_4 leak localization.

The gas distribution maps generated in this work represent a snapshot of the gas distribution taken during the exploration time. As future work, the data collected by the robotic platform can be used to create a model that predicts the methane emission rates of a given landfill site at different temporal resolutions. The creation of such models is of high interest for biogas producers and the waste management industry.

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