Gas Sensing Mobile Robot: A Review

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***Abstract*—Mobile robot applications are required in various hazardous fields to reduce human casualties. One of the most demanding applications is gas sensing mobile robot. Since the hazardous chemical compound is undetectable by humans, autonomous mobile gas sensors are needed. Over the past few decades, various attempts to incorporate gas sensor on mobile robots are reported. Gas source localisation and gas distribution mapping are the two mainly focused scope of research. This paper presents the earliest works and recent development in gas sensing mobile robots.**

***Index Terms*—Bio-inspired Algorithm; Gas Sensor; Mobile Robot; Gas Distribution Mapping; Gas Source Localization.**

I. Introduction

The need for odour-sensing applications has been triggered due to air contamination diseases and deaths recorded for the past few decades [1]. Industrial facilities or even research institutions, mainly related to chemical works often face casualty due to unidentified chemical leakages. Since most of the hazardous chemical compounds are in gas form, odourless and colourless, humans are unable to identify a potential leakage. These tragedies led to the deployment of static gas detectors in an indoor environment to continually monitor possible contamination breakout and chemical compound leakages [2]. However, this method is impractical due to the nature of gas sensors where the gas molecules need to be in contact with the reactive surface of the sensor to produce response [3]. Therefore, the information of gas concentration or reading is only valid for a limited space around the location of the gas sensor. As the sensing capability is limited in range, a large number of sensors are required to cover relatively large environment efficiently.

Thus, the mobile-based olfactory application became a practical solution. Gas sensors are combined with the mobile robot and dispatched in a designated area to continually monitor the environment for the presence of gas. Unlike static gas sensors, mobile gas sensors can provide a more accurate representation of gas distribution due to the ability to move from one location to another. Besides, mobile robot with gas sensor holds an upper hand compared to humans, since the mobile robot can explore hazardous environments, has better heat tolerance, and does not show exhaustion[4].

As the field of mobile olfaction gains attention, several research directions have emerged including localisation of the gas source and spatial representation of the gas distribution. This paper discusses the reported works of gas sensing mobile robots, including state-of-the-art approaches. Significant solutions for mobile olfaction problems are also highlighted. Finally, possible research gaps in mobile olfaction are also discussed in this paper.

II. Gas Sensing

The development of gas sensing mobile robot is now possible due to the recent advancement in chemical sensor development. Various types of gas sensors have emerged and are available commercially. However, each type of sensors exhibits different characteristics based on the sensing material used in the sensors.

Followings are the types of gas sensor available:
1. Metal Oxide (MOX)
2. Polymer
3. Photo Ionization Detectors (PID)
4. Pellistors
5. Optical
6. Gas Chromatography (GC)

One the most widely used gas sensor is MOX type. This sensor can react to different types of gas at different temperatures ranging from 200°C to 500°C[5]. Due to this, the MOX gas sensor requires heaters and consumes relatively high power to operate. On the other hand, polymer gas sensor can detect volatile organic compound (VOC) that may not be detected by MOX gas sensor. This sensor absorbs the gas molecules and responses by changing the polymer's electrical properties.

Photo Ionization Detectors (PID) senses gas by ionising the gas with ultraviolet light. Then, the ions are discharged through electrodes producing a detectable current [6]. Pellistors are a calorimetric gas sensor which detects the changes in heat due to changes in concentration. This is usually done by using a thermistor or a platinum wire. The heat changes occur due to the changes in thermal conductivity of the gas flow [7]. The optical-based gas sensor uses optical properties of gases, such as light absorption, photo fluorescence, diffraction and reflection to generate a response. This method requires preparation of spectrometry to operate [8].

In recent years, MOX gas sensor has dominated the research field of gas sensing mobile robots. This sensor has been widely used by many researchers in their works [9-11]. Although MOX gas sensor consumes relatively high power and has low selectivity, it is more practical to be deployed on mobile robots. This is due to the lower deployment cost, less complexity regarding electronics, and high reliability. Fig. 1 illustrates the typically used MOX gas sensor on mobile robots.

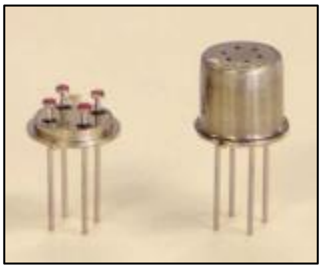

Figure 1: MOX gas sensor (TGS series) [44].

III. GAS SOURCE LOCALIZATION

The principal objective of implementing gas sensor on a mobile robot is to trace and locate the source of a volatile chemical distributed in an environment. This task is defined as gas source localisation [9]. Earlier researchers suggested that gas source localisation can be achieved by performing three subtasks, starting from plume finding, followed by plume tracking, and finally source location declaration [12]. This strategy was adapted from living organism, where the olfactory behaviour of animals and insects is mimicked using mobile robots. For example, male moths can find their mates by tracking and following the pheromones released by female moths. Trained police dogs, on the other hand, can pursue criminals. Many successful bio-inspired algorithms have been reported.

A. Chemotaxis

Chemotactic behaviour is the act of moving along the concentration gradient of a chemical. This behaviour is exhibited by most animals to search food and mates. Similarly, a pair of sensors is equipped with a mobile robot, and a measured gas concentration gradient is used to steer the mobile robot towards the gas source. An example of the chemotactic based mobile robot is shown in Fig. 2. One of the notable works was presented in [13], where the location of the gas source was successfully identified. In this work, the researchers found that higher concentration was detected closer to the gas source. Similar work was also presented by [14], where several chemotaxis algorithms were compared. This work proved that Braitenberg vehicle followed a shorter path to the gas source. However, it is least reliable due to lack of airflow information.

Apart from that, another simple approach was also reported based on gradient climbing behaviour of *E. coli*. The work presented in [15] became the starting point of this approach. Simulation work was presented in [16], claimed as Biased Random Walk (BRW). The result shows that this algorithm was ineffective due to fluctuation in the gas dispersion. The same result was obtained in [10] and [14] with real-world implementation.

Later, swarm-based approaches were also attempted, mainly to improve the gas source localisation problems reported by the non-swarm approach. This strategy was also bio-inspired, mainly from organisms living in a colony. One of the important approaches was Particle Swarm Optimization (PSO). A simulation work was presented in [17] and [18], where PSO was compared with BRW. The simulation was performed under turbulent dominated gas dispersion. It was proven that PSO has better performance in vigorous environment condition. This work was further improved in [19] by proposing a modified PSO algorithm. Another improvement of PSO was presented in [20], known as Explorative PSO (EPSO). In this work, the mobile robots are configured to avoid previously explored location to prevent the swarm from being trapped in local maxima. A convincing result was presented showing that EPSO performs better than PSO.

Another bio-inspired algorithm adapted from ants social foraging behaviour was later introduced. This strategy was altered to solve the gas source localisation task, known as ant colony algorithm [11]. In this work, mobile robots are divided into two groups, searchers and residents. The searcher is responsible for tracking and moving toward higher gas concentration areas. When a possible source location is found, the searcher becomes resident. Meanwhile, another resident with lower gas concentration will be appointed as searcher again. The process is repeated until all robots converge towards one location, which is declared as the gas source.

Recently, several works are reported to improve the gas source localisation task further. In [21], a hybrid algorithm was introduced by combining PSO with Bacterial Foraging Optimization (BFO) to localise the gas source. This work manages to eliminate robots from being trapped in local minimum by adapting elimination-dispersal operation of BFO. The results showed that PSO-BFO algorithm could localise gas source with higher success rate and shorter time. Another work considered obstacles around the environment by incorporating path planning algorithm with BFO. A Gaussian cost function was introduced to determine the shortest path from an unknown position to a target position in the presence of obstacles. This work was proven to be less complicated and able to localise gas source faster compared to other well-known algorithms [22].

Figure 2: Mobile robot equipped with a pair of gas sensors [13].

B. Anemotaxis

Unlike chemotactic behaviour, anemotaxis utilises additional information, which is airflow measurement to localise the gas source. Since volatile chemical molecules are carried by moving air, following upwind direction can theoretically lead a mobile robot to the source. Thus, mobile robots were equipped with airflow sensors (Fig. 3), which are inspired by plume tracking capability of moths.

One of the earliest works was reported in [23] implementing dung beetle algorithm. This work claims that the algorithm only works if the robot starts within the plume area. Several failures were also highlighted due to high variations in wind flow. Later, the algorithm was enhanced in [24] using a state machine to improve the plume tracking task.

This improvement led to less failure rate of the gas localisation task. A similar approach was also presented by [14] with a comparison to *E. coli* algorithm, showing that anemotaxis are more reliable. An enhanced method was also presented using both chemical concentration and anemometric reading [25]. This work calculated vectors to the centre of the plume and the gas source, providing a multiphase algorithm to track the gas source.

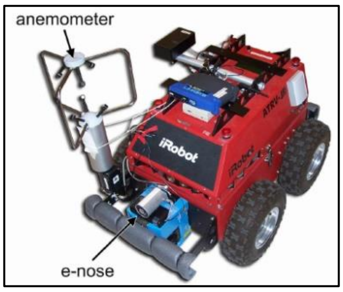

Figure 3: Mobile robot equipped gas sensor and anemometer [39].

Another commonly used and most studied approaches were silkworm moth algorithm. The initial work was implemented by [26] and later adapted in comparison work in [10] and [14] under turbulent dominated gas dispersion. Following these researchers, weak airflow was also considered in improving the silkworm algorithm [27]. By removing anemometric information, a fixed motion pattern towards higher concentration level was implemented in this work. The adapted algorithm has improved the performance of plume tracing task compared to random search algorithms.

A few casting algorithms were also introduced namely casting, surge-cast, and spiral surge. The initial work was focused on casting and spiral surge algorithms [28]. Later, a new algorithm was implemented in a comparative work [29]. These algorithms manage to locate the gas source successfully under turbulent dominated dispersion. This approach was also proven to be more practical in implementing on mobile robots.

Genetic Algorithm (GA) is another approach emerged with a solution to optimisation problems. GA has been implemented in both turbulent dominated and diffusion dominated gas dispersion to localise gas source [30]. Anemometric and chemical information were used in this algorithm to de-randomise the possible solutions. Through simulation, the ability to localise gas source using both single robot and multiple robots were shown in this work.

Moreover, the swarm-based approach was also reported in previous works [31] and [32]. Silkworm moth algorithm was used as the fundamental in these works, where the robots perform upwind surge when gas is detected. Other robots will be attracted through an attractive virtual force by the robot which detects the gas. Both simulation and real-world works showed that this approach shortened the search time to localise the gas source.

Recently, another novel approach was introduced [33] which can estimate the distance of the mobile robot to a gas source. Rapid change in the sensor signal ("bouts") and the wind directions are combined to guide the Gaussian regression to interpolate distance estimates. The proposed method can perform better under turbulent conditions to localise the gas source.

IV. Gas Distribution Mapping

In specific applications, the exact location of the gas source is not required. However, the distribution of the gas in space is needed. Gas distribution mapping (GDM) is a task of representing how gases spatially dispersed within an environment. This task can also be achieved through mobile robots exploring an environment by carrying a gas sensor. Similar to the static gas sensor problem, the challenge in building a GDM lies in the gas sensor itself, where the measurement of the gas sensor is only valid for limited space around the point of measurement.

The earliest breakthrough in GDM was reported in [34] by proposing a statistical approach. This works introduced an extrapolation algorithm by convolving gas sensor readings with a Gaussian kernel. In this work, the environment is represented as grid map, and each grid holds a convolved value of the gas sensor measurement taken at a random location. This method held a significant advantage where the mobile robot does not need to explore every part of the environment to construct a GDM fully. Moreover, concentration maximum was used to obtain an approximate estimate of the gas source location. The method was then adapted in the case of multiple gas sources [35], where the gas source was able to be localised with higher certainty. Besides, this approach was also extended to the case of three-dimensional GDM [36]. This work implemented a tri-variate Gaussian kernel to model gas dispersion. To achieve this, three gas sensors were attached to the mobile robot at a different height.

However, these works assumed that the position of the mobile robot is known and the map is built before GDM. In the case of the unknown position of the mobile robot, simultaneous localisation and mapping (SLAM) were integrated to GDM [37]. This work implemented the Rao-Blackwellized particle filter approach to estimate the mobile robot position and map of the environment, while simultaneous build GDM as the mobile robot explores the environment.

Later, uncertainty estimation was incorporated to GDM by accounting predictive variance. Gaussian process mixture model (GPM) was proposed by assuming gas distribution modelling as a regression problem [38]. This work reported that prediction of uncertainty for GDM improves the accuracy of the gas concentration prediction. Following this approach, two parallel estimation processes was carried out separately for mean and variance prediction of GDM, known as the kernel DM+V algorithm [39]. This approach pointed out the previous work that variability lies in the gas sensor readings, not on the uncertainty in the estimation process. Although both works [38] and [39] produced similar GDM, the kernel DM+V holds the upper hand in handling more massive datasets with more straightforward learning procedure. More recently, another approach to variance prediction was presented using sparsified Kalman filter [40].

There are also several other variables that influence gas dispersal, namely wind, pressure, temperature and humidity. Several works were also reported which took these variables into account. Adapting the kernel DM+V algorithm, wind information was taken into account to build GDM using kernel DM+V/W algorithm [41]. This approach used the measured wind vector to alter the shape of the bivariate Gaussian kernel. The outcome of this approach produced a notable improvement in GDM compared to previous methods. An example result is shown in Fig. 4. The similar work was also further extended to a three-dimensional representation of GDM [42]. This work has taken the wind vector to improve the multivariate Gaussian kernel shape.

Similar to the stated variable which effects GDM, the physical nature of the environment was not taken into account while building GDM. A structured environment consists of walls, corridors and rooms which affect the dispersal of gas. In previous approaches, a gas concentration measurement taken from one location was directly correlated to another location without considering the presence of physical obstacles in between. Apart from that, another question raised was the similarity between two measurements taken from the same location at different times. This is due to the vanishing nature of gas. Most recently, both problems were considered, and a novel approach was introduced in GDM [43]. This work employed Gaussian Markov Random Field (GMRF) by accounting obstacles in the environment and "age" of the measured gas concentration which suits the characteristic of GDM. The results of this approach provide a better representation of gas dispersal in a structured indoor environment.

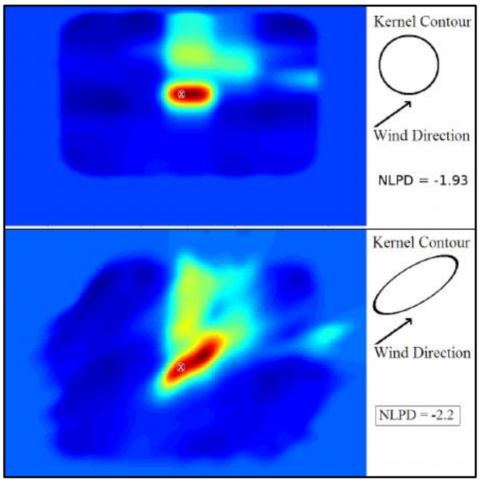

Figure 4: Improved GDM with wind information [41].

V. RESEARCH GAPS

Although various approaches towards mobile olfaction have been reported, there is always room for improvement to achieve an ideal gas sensing mobile robot which can work in real environment. Reported approaches to date have been only considering gas sources placed on the floor of the environment. However, in the real world, possible gas leakages could occur in various places which are higher than the floor, such as pipelines in ceilings. A very few approaches towards this direction is reported so far. Apart from that, the presence of obstacles in the environment is another challenging problem which remains open. To the best knowledge of the author, only one work is presented accounting the obstacles in the environment [43].

The performance of the gas sensor is another issue that was brought up by many researchers. As mentioned previously, MOX gas sensor is the favourite choice in mobile olfaction. However, this sensor has a slow recovery time which becomes one of the challenges in mobile olfaction. Although several reported approaches accounted this issue and managed to compensate the recovery time, a revolutionary sensor with faster response and recovery time will further improve the mobile olfaction research.

Another notable problem faced by most researchers is the validation of the experiment conducted. Currently, there is no standardised framework to verify the results in mobile olfaction due to the lack of ground truth information. Development of a standardised verification framework is highly essential in this research field.

VI. CONCLUSION

In this paper, significant contributions towards mobile olfaction have been reviewed. Many successful works have been reported on gas source localisation and gas distribution mapping. Previously, most of the works are presented through simulations and later directed towards the real-world application. The gaps exist in this research field were also highlighted, and possible directions were also stated. In the near future, gas sensing mobile robot may commercially available for humans.

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