Gas source localization accuracy: A comparison between conventional, weighted arithmetic mean and kernel-based gas distribution mapping methods in small indoor area

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Abstract. This work focuses on comparing gas source localization accuracy of three types of gas source localization methods which are the conventional method, weighted-averaging mean method and variance map from DM+V method. Gas source localization accuracy in this work means the distance error between the calculated source location and the actual source location. All methods were implemented offline using the measurements collected from real-time gas source localization experiments that were done beforehand. The dataset consists of gas sensor measurements, and mobile robot’s location in a 3m by 6m test area. The goal of the work is to shine a light on why recent works in the field are more focusing on improving probabilistic and map-based algorithms. This work also shows how the kernel size of kernel-based gas distribution mapping might affect the gas source localization accuracy in a small indoor area.

1. Introduction
Gas source localization in a way is a problem of calculating the exact gas source location in the environment. Gas source localization using mobile robots is still a fledgling field which started in the early 90s where researchers began to build mobile robots that can find the source of chemical releases [1].

A problem that continuously occurred to researchers in the past when trying to tackle the gas source localization problem is that the gas plume is circulated through wind which is turbulent in nature. This makes it difficult for researchers to accurately calculate gas source location because of the gas concentration is not a smooth gradient from the source towards the open environment. Instead, it is intermittent and often fluctuating. It was often found that the highest concentration patch in the environment is not the actual source location [2].

Gas source localization tasks are usually divided into three sub-tasks [3] as below:
a) Gas plume searching: Searching the environment for the presence of gas plumes.
b) Gas plume tracing: Tracing the found gas plume towards the gas source.
c) Gas source declaration: Declaring that the source is found because the mobile robot has reached the vicinity of the source or the final location of the source has been calculated.

As mentioned above, the third subtask which is gas source declaration is quite vague between research groups. The traditional way of declaring the source is by manually observing the mobile robot reached the vicinity of the gas source location [4]. This method is acceptable as early works in the field were mostly focusing on testing gradient-based or bio-inspired algorithms capability to find and trace gas plumes towards the source. But in real life implementation, it is ideal for the mobile robot to be fully autonomous and aware that it has found the gas source or calculate where the source location is.

The focus of this work is to compare the accuracy of gas source localization or in other words, the distance error from the calculated gas source location to the actual gas source location of three methods that can be used to solve gas source localization problem. The three methods are described in Section 3. The main goal of this work is to show the significance developing new methods for gas source declaration and to shine a light on why modern works in this field are now more focusing on improving probabilistic and map-based algorithms.

2. Literature Review

The first impactful work on gas source localization using a mobile robot was done by equipping a mobile robot with 4 gas sensors at 4 different positions. The robot will stop and take gas sensor measurements before taking steps towards the direction of the highest recorded measurement gas sensor [1]. The process was repeated and if the robot managed to get into the vicinity of the gas source, the experimental run was marked as a success and the mobile robot’s run is terminated.

Gas source declaration by terminating the robot when the robot gets near the gas source continued for quite some time [4-7]. However, the researchers were not specifically focused on gas source declaration but rather to show that the implemented gas plume searching, and gas plume tracing techniques are working as intended which is to move the mobile robot towards the gas source. Moreover, hardware limitations at the time are preventing researchers from implementing more complex algorithms. With advancements made in terms of hardware in recent years, algorithms or methods with high computing cost are now possible to be implemented on mobile robots.

High computing cost algorithms such as probabilistic-based gas source localization was discussed as an idea in 2007. It was demonstrated that gas source localization task can be performed by mobile robots using an infotactic approach rather than gradient climbing [8]. Infotactic algorithms are typically Bayesian inference methods where the mobile robot holds a probability distribution of where the gas source location is. The probability distribution keeps updating when more information is made available. Typically, the information is used to build a gas distribution map (GDM). The map is updated continuously until the probability of a certain point in the map increases to 1 [9-11]. Moreover, the information can be used to guide the robot towards the gas source instead of map building. This was specifically done in 2011 but with a particle filter-based algorithm instead of Bayesian inference-based algorithm where the work shows that the mobile robot performed a searching and exploratory-like behavior while also calculating the gas source location [12].

Breakthrough in kernel-based GDM method to solve gas source localization were demonstrated in 2004 [13]. More importantly, in 2007 the method was implemented alongside simultaneous localization and mapping (SLAM) [14]. Results from the work shows significant potential as the actual gas source location corresponds to the highest estimated concentration. Improvements were made by the introduction of Kernel DM+V where variance estimation is computed to build a variance map [15]. The work shows that variability lies with the gas sensor measurements which makes the variance map is more accurate on estimating the gas source location. Several work on DM+V were
done in the following years to improve it such as Kernel DM+V/W [16] where wind information is added and also a 3-dimensional GDM [17].

2.1. Related Works
This work is heavily influenced by previous works done by the research group in CEASTech. A 6 by 3-meter testbed in an open indoor area were used specifically for real-time gas source localization experiments [18]. A large gas sensor array (LGSA) was built specifically to collect gas sensor measurements during an experiment. The sensor array covered the experimental area and the collected data can act as ground truths. Furthermore, the area is covered by 4 mounted ceiling cameras that can track mobile robot’s location in the area [19]. The overview of the testbed and its system is shown in Figure 1. Multiple gas source localization works have been done previously utilizing the testbed to study behavior-based algorithms [20,21,22] and gas dispersion with induced airflow on the testbed [23]. Moreover, CEASTech have also been working on integrating simultaneous localization and mapping (SLAM) with GDM in recent years [24] that have shown potential to localize gas source locations in real-world scenarios.

![Figure 1](image_url)

**Figure 1.** a) shows the layout of the LGSA where 72 MOX gas sensors arranged in 12 rows covering the whole area of the testbed and where each row consists of 6 MOX gas sensors while b) shows the mobile robot testbed consisting of ceiling mounted cameras, gas sensors, sensor boards and wireless modules.

3. Methodology
With the focus of this work is to compare gas source localization accuracy of three methods, this work was based on the dataset from gas source localization experiments on the testbed shown in Figure 1 with no obstacles or induced wind [18] using a mobile robot that implemented behavior-based or reactive gradient climbing algorithms [21] while performing gas source localization tasks. The behavior-based algorithm used for this work is explained in Section 3.1. During the experiment, ethanol gas was released into the test area at location \((x,y) = (150,220)\).

From the dataset, we obtained the mobile robot’s location and gas sensor’s measurements. Using the data, we performed 3 methods of gas source localization offline to compare its distance error from actual gas source location using the average measurements of the two FIGARO TGS2600 metal oxide gas sensors that were installed on the mobile robot. The three methods are conventional, weighted averaging mean and variance map of DM+V which are thoroughly described in Section 3.2.
3.1. Zig-Zag and Braitenberg Fusion
The Zig-Zag and Braitenberg algorithms were implemented on a mobile robot. Each of the algorithm is triggered during the experiment based on the sensor signal value \( s \) in a state machine manner. Sensor signal value is calculated from Equation (1) where \( R_0 \) represents the baseline resistance of the gas sensor taken at the start of an experimental run and \( R_s \) is the resistance of the gas sensor calculated at time \( t \).

\[
s = \frac{\Delta R}{R_0} = \frac{(R_0 - R_s)}{R_0} = 1 - \frac{R_s}{R_0}
\]

The mobile robot performed the Zig-Zag behavior when \( s \) is below than 0.3 and Braitenberg when it’s higher which means that the mobile robot will perform a searching like behavior when it is not detecting high gas plume concentration and a gas plume tracing behavior when its sensors measured a high gas concentration. Example of the mobile robot’s behavior with the implementation of this algorithm is depicted in Figure 2 where it shows that the mobile robot lingered around the areas where the gas concentration is higher.

3.2. Gas Source Localization Method
As calculating the gas source location, three methods were chosen for this work to compare its accuracy. The three methods are as follows:

a) Conventional method: Taking the location of the highest recorded gas sensor measurement.

b) Weighted arithmetic mean: Calculate the location of the gas source by applying sensor signal values as weights.

c) DM+V variance map: Taking the location of the highest variance value within the testbed as gas source location.

More details on weighted arithmetic mean method and DM+V variance map method is presented in Section 3.2.1 and 3.2.2.

3.2.1. Weighted Averaging Mean. By applying the sensor signal values to act as weights to the robot’s location, a centroid is possible to be calculated. This strategy is a simplified version of a gas source localization algorithm based on particle filter in wireless sensor network which was done by calculating the source location using information gained by multiple static gas detectors [25]. A non-empty set of data consists of \( x \)-axis and \( y \)-axis coordinates denoted as \( \{x_1, x_2, x_3, ..., x_n\} \) and
\{y_1, y_2, y_3, \ldots, y_n\}. A set of sensor measurements taken at the coordinate such as sensor voltages or signal values act as weights can be denoted as \{w_1, w_2, w_3, \ldots, w_n\}. Equation (2) and Equation (3) denotes the calculation of the weighted mean where \(x_p\) and \(y_p\) is the predicted x-axis and y-axis location of the gas source. In this work, \(w\) is sensor signal value \(s\) where only \(s \geq 0\) is taken into consideration.

\[
x_p = \frac{\sum_{i=1}^{n} s_i x_i}{\sum_{i=1}^{n} s_i}
\]

\[
y_p = \frac{\sum_{i=1}^{n} s_i y_i}{\sum_{i=1}^{n} s_i}
\]

3.2.2. DM+V Variance Map. Kernel DM+V [15] models the gas dispersion using a univariate Gaussian function \(N\) to convolve the sensor measurement \(r_i\) at location \(x_i\) across a grid map expressed by Equation (4). The \(\text{dist}(k)\) is defined as the Euclidian distance of \(k\)th cell in a grid map from point \(x_i\).

\[
N(\text{dist}(k), \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(\text{dist}(k))^2}{2\sigma^2}}
\]

A weight map, \(\Omega_k\) and a weighted reading \(R_k\) for \(n\) sensor readings are computed by Equation (5) and Equation (6) respectively. The \(\sigma\) is the kernel width which means the amount of extrapolation of the gas sensor measurement \(r_i\). The likelihood of \(r_i\) to be expanded wider across the grid map is higher with the increase of \(\sigma\). The confidence of estimation of cell \(k\) is obtained by normalizing \(\Omega_k\) to a confidence map, \(\alpha_k\) with scaling parameter, \(\sigma_a\) denoted by Equation (7).

\[
\Omega_k = \sum_{i=1}^{n} N(\text{dist}(k), \sigma)
\]

\[
R_k = \sum_{i=1}^{n} N(\text{dist}(k), \sigma) \cdot r_i
\]

\[
\alpha_k = 1 - e^{-\frac{(\Omega_k)^2}{\sigma_a^2}}
\]

Mean concentration map can be calculated using Equation (8) where \(r_o\) is the average of all gas sensor measurements. Variance map \(\nu_k\) is computed from weighted variance \(V_k\) from Equation (9) and Equation (10) respectively where \(k(i)\) is the cell of gas sensor measurement and point \(x_i\), \(r_{k(i)}\) is the mean value of cell \(k\) and \(\nu_o\) is the average overall variance computation. \(v_i\) represents the sensor variability at every measurement point. The cell with the highest \(\nu_o\) is the predicted gas source location.

\[
r_k = \alpha_k \frac{R_k}{\Omega_k} + (1 - \alpha_k)r_o
\]

\[
V_k = \sum_{i=1}^{n} N(\text{dist}(k), \sigma) \left( r_i - r_{k(i)} \right)^2
\]
\[ v_k = \alpha_k \frac{V_k}{\Omega_k} + (1 - \alpha_k)v_o \] (10)

4. Results

A total of 20 experimental runs were done during the experiment where the mobile robot performed gas source localization tasks using the algorithm in Section 3.1. The collected data was then used by to estimate the gas source location with the 3 methods mentioned in Section 3.2. The accuracy of gas source localization or the distance error between the estimated location and actual gas source location were calculated using the 3 methods. The results are shown in Table 1.

### Table 1. Distance error of the estimated source location using the three methods.

| Run Number | Variance Map (\(\sigma=0.1\)) | Distance Error (cm) | 
|------------|-------------------------------|---------------------| 
|            |                               | Weighted Arithmetic Mean | Conventional |
| 1          | 31.89                         | 53.43               | 25.50        |
| 2          | 57.71                         | 62.56               | 70.08        |
| 3          | 165.53                        | 145.19              | 186.34       |
| 4          | 72.20                         | 111.45              | 227.75       |
| 5          | 81.74                         | 81.67               | 81.42        |
| 6          | 37.12                         | 53.40               | 40.71        |
| 7          | 53.94                         | 12.45               | 44.92        |
| 8          | 55.80                         | 68.79               | 43.27        |
| 9          | 56.30                         | 98.60               | 82.15        |
| 10         | 33.29                         | 17.65               | 22.15        |
| 11         | 47.43                         | 15.50               | 20.91        |
| 12         | 99.13                         | 140.41              | 49.80        |
| 13         | 166.41                        | 20.34               | 97.77        |
| 14         | 200.94                        | 107.60              | 70.78        |
| 15         | 159.14                        | 67.32               | 57.14        |
| 16         | 81.15                         | 23.39               | 91.24        |
| 17         | 20.62                         | 42.75               | 66.36        |
| 18         | 39.20                         | 73.24               | 38.93        |
| 19         | 37.00                         | 86.46               | 54.74        |
| 20         | 17.49                         | 19.38               | 43.83        |

| Average (cm) | Distance Error (cm) | 
|--------------|---------------------| 
| 75.70        | 65.08               | 70.79        |

From Table 1, it can be deduced that in a less complex small indoor area, weighted arithmetic mean method in general is sufficient enough for accurate gas source localization. This could be best implemented on mobile robots when testing out behavior-based path planning algorithms as it is not computationally taxing. Table 1 also clearly shows the problem that researchers of this field have been facing where the location of the highest average gas measurement is not always near the actual gas source location as in Run 3 and 4, the error is around 2 meters.

Moreover, results have shown that the variance map method is in average the least accurate of the three, but it is the most accurate in 7 out of 20 runs (Run 2, 4, 6, 9, 17, 19 & 20). From experimenting with building the variance map of DM+V, we have noticed that the kernel size played an important part in getting accurate gas source location estimation. Table 2 shows how the kernel size affects the accuracy of gas source localization. From Table 2, it can be seen that the best kernel size is on a case by case basis. Kernel sizes larger than 0.4 is not shown as the interpolation area becomes too large and the highest variance are often out of the test area boundaries.
Table 2. Distance error of the estimated source location using variance map of multiple kernel sizes.

| Run Number | $\sigma=0.1$ | $\sigma=0.2$ | $\sigma=0.3$ | $\sigma=0.4$ |
|------------|--------------|--------------|--------------|--------------|
| 1          | 31.89        | 48.33        | 58.82        | 72.78        |
| 2          | 57.71        | 69.12        | 77.47        | 28.23        |
| 3          | 165.53       | 98.29        | 98.08        | 230.27       |
| 4          | 72.20        | 239.24       | 238.84       | 265.71       |
| 5          | 81.74        | 75.03        | 69.89        | 64.20        |
| 6          | 37.12        | 26.93        | 24.74        | 16.40        |
| 7          | 165.53       | 98.29        | 98.08        | 230.27       |
| 8          | 53.94        | 57.72        | 73.76        | 74.97        |
| 9          | 56.30        | 149.16       | 149.86       | 154.54       |
| 10         | 33.29        | 44.05        | 43.27        | 37.34        |
| 11         | 47.43        | 44.55        | 43.01        | 36.50        |
| 12         | 99.13        | 58.52        | 78.16        | 74.33        |
| 13         | 166.41       | 106.51       | 112.73       | 139.09       |
| 14         | 200.94       | 198.81       | 191.08       | 53.26        |
| 15         | 159.14       | 130.10       | 87.80        | 76.85        |
| 16         | 81.15        | 50.99        | 47.07        | 39.56        |
| 17         | 20.62        | 16.76        | 31.38        | 47.42        |
| 18         | 39.20        | 39.62        | 45.45        | 55.76        |
| 19         | 37.00        | 150.56       | 51.62        | 49.48        |
| 20         | 17.49        | 34.99        | 25.94        | 26.93        |
| **Average (cm)** | **75.70** | **86.44** | **82.20** | **81.69** |

5. Conclusion & Future Work
The accuracy of gas source localization via kernel-based gas distribution mapping is influenced by the kernel size. Other works have also shown that the kernel shape and size can be manipulated with additional information such as wind [16], temperature and humidity [26]. The shape of the environment such as walls and obstacles should also be taken into consideration when determining the kernel size as to avoid gas sensor measurements being interpolated out of bounds. It can be said that the gas distribution mapping method has a lot of potential to be further explored.

References
[1] Rozas R, Morales J and Vega, D 1991 Artificial smell detection for robotic navigation Fifth Int. Conf. on Advanced Robotics’ Robots in Unstructured Environments pp 1730-1733
[2] Fukazawa Y and Ishida H 2009 Estimating gas-source location in outdoor environment using mobile robot equipped with gas sensors and anemometer SENSORS, 2009 IEEE pp 1721-1724
[3] Chen X X and Huang J 2019 Odor source localization algorithms on mobile robots: A review and future outlook Robotics and Autonomous Systems 112 pp 123-136
[4] Lilienthal A J and Duckett T 2003 Experimental analysis of smelling Braitenberg vehicles IEEE int. conf. on advanced robotics (Coimbra) 1 pp 375-380
[5] Ferri G, Caselli E, Mattoli V, Mondini A, Mazzolai B and Dario P 2009 SPIRAL: A novel biologically-inspired algorithm for gas/odor source localization in an indoor environment with no strong airflow Robotics and Autonomous Systems 57 pp 393-402
[6] Sandini G, Lucarini G and Varoli M 1993 Gradient driven self-organizing systems Proc. of Int. Conf. on Intelligent Robots and Systems 1 pp 429-432
[7] Kuwana Y, Shimoyama I and Miura H 1995 Steering control of a mobile robot using insect
antennae Proc. Int. Conf. on Intelligent Robots and Systems. Human Robot Interaction and Cooperative Robots 2 pp 530-535
[8] Vergassola M, Villermoux E and Shraiman B I 2007 ‘Infotaxis’ as a strategy for searching without gradients Nature 445 pp 406-409
[9] Blanco J L, Monroy J G, Lilienthal A and Gonzalez-Jimenez J 2013 A kalman filter based approach to probabilistic gas distribution mapping Proc. of the 28th Annual ACM Symposium on Applied Computing pp 217-222
[10] Grünbaum D and Willis M A 2015 Spatial memory-based behaviors for locating sources of odor plumes Movement ecology 3 11
[11] Hajieghrary H, Hsieh M A and Schwartz I B 2016 Multi-agent search for source localization in a turbulent medium Physics Letters A 380 pp 1698-1705
[12] Li J G, Meng Q H, Wang Y and Zeng M 2011 Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm Autonomous Robots 30 pp 281-292
[13] Lilienthal A and Duckett T 2004 Building gas concentration gridmaps with a mobile robot Robotics and Autonomous Systems 48 pp 3-16
[14] Lilienthal A J, Loutfi A, Blanco J L, Galindo C and Gonzalez J 2007 A rao-blackwellisation approach to gdm-slam: Integrating slam and gas distribution mapping 3rd European conf. on mobile robots pp 126-131
[15] Lilienthal A J, Reggente M, Trincavelli M, Blanco J L and Gonzalez J 2009 A statistical approach to gas distribution modelling with mobile robots-the kernel dm+ v algorithm Int. Conf. on Intelligent Robots and Systems pp 570-576
[16] Reggente M and Lilienthal A J 2009 Statistical evaluation of the Kernel DM+ V/W algorithm for building gas distribution maps in uncontrolled environments Procedia Chemistry 1 pp 481-484
[17] Reggente M and Lilienthal A J 2010 The 3d-kernel dm+ v/w algorithm: Using wind information in three dimensional gas distribution modelling with a mobile robot SENSORS, 2010 IEEE pp. 999-1004
[18] Syed Zakaria S, Visvanathan R, Kamarudin K, Ali Yeon A, Zakaria A and Kamarudin L 2015 Development of a Scalable Testbed for Mobile Olfaction Verification Sensors 15 pp 30894-30912
[19] Visvanathan R, Mamduh S M, Kamarudin K, Yeon A S A, Zakaria A, Shakaff A Y M and Saad F S A 2015 Mobile robot localization system using multiple ceiling mounted cameras 2015 IEEE SENSORS pp 1-4
[20] Yeon A S A, Visvanathan R, Mamduh S M, Kamarudin K, Kamarudin L M and Zakaria A 2015 Implementation of behaviour based robot with sense of smell and sight Procedia Computer Science 76 pp 119-125
[21] Yeon A S A, Kamarudin K, Visvanathan R, Zakaria S M M S, Zakaria A and Kamarudin L M 2018 Gas Source Localization via Behaviour Based Mobile Robot and Weighted Arithmetic Mean IOP Conf. Series: Materials Science and Engineering 318 012049
[22] Mamduh S M, Kamarudin K, Shakaff A Y M, Zakaria A, Visvanathan R, Yeon A S A and Nasir A S A 2018 Gas Source Localization using Grey Wolf Optimizer J. of Telecommunication, Electronic and Computer Engineering 10 pp 95-98
[23] Mamduh S M, Kamarudin K, Visvanathan R, Yeon A S A, Shakaff A Y M, Zakaria A and Abdullah A H 2017 Gas dispersion with induced airflow in mobile olfaction testbed AIP Conf. Proc. 1808 020051
[24] Kamarudin K, Md Shakaff A Y, Bennetts V H, Mamduh S M, Zakaria A, Visvanathan R and Kamarudin L M 2018 Integrating SLAM and gas distribution mapping (SLAM-GDM) for real-time gas source localization Advanced Robotics 32 pp 903-917
[25] Li Q, Liu Z and Xiao X 2015 A gas source localization algorithm based on particle filter in wireless sensor network Int. J. of Distributed Sensor Networks 11 874532
[26] Kamarudin K, Bennetts V H, Mamduh S M, Visvanathan R, Yeon A S A, Shakaff A Y M and Kamarudin L M 2017 Cross-sensitivity of metal oxide gas sensor to ambient temperature and humidity: Effects on gas distribution mapping *AIP Conf. Proc.* **1808** 020025