Multi-Modal Robotic Platform Development for Odor Source Localization

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***Abstract*—This paper discusses customizing a popular robot development platform "Turtlebot3" for Odor Source Localization (OSL) task. OSL technology allows a robot to locate and navigate to odor sources in an unknown environment. Turtlebot3 is an agile robot platform that includes Raspberry Pi for on-device computation and an Open-source Control module for ROS (OpenCR) board for additional sensor connection. It runs on "Robot Operating System (ROS)" that allows it to run complex algorithms that can subscribe and publish to specific robot sensors and components. In combination, this robotics platform can be customized to perform a wide variety of robot tasks. This paper focuses on the additional olfactory sensor installation for the OSL experiment. It also discusses an olfactory-based navigation algorithm named moth-inspired algorithm for OSL task. The algorithm was applied to real-world experiments with varying conditions. The experiments show that the moth-inspired algorithm successfully navigates to the odor source in laminar airflow environments. The paper also discusses the future scope of adding vision sensors and machine learning algorithms.**

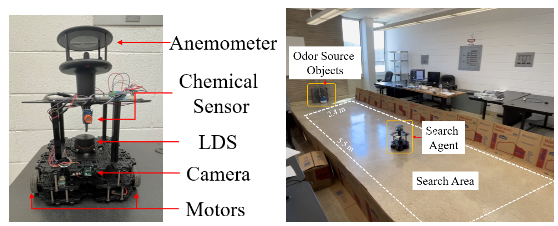
***Index Terms*—Odor source localization, moth-inspired algorithm, Turtlebot3, Robot Operating System, Multi-modal robotics.**

I. Introduction

Animals interact with the external environment using sensory systems – visual, auditory, olfactory, gustatory, tactile, etc. These systems help animals sense and interpret the environment and perform activities like foraging, mating, evading predators, etc. for survival. A similar strategy of using multiple sensors is also used in robotics for sensing and acting in unknown environments. A robot equipped with a visual sensor (camera), olfactory sensor (e.g., chemical sensor), tactile sensor (e.g., touch sensor, airflow detection sensor), etc. can sense, navigate and manipulate unknown environments to achieve specific goals.

Olfaction is an important sensing system for robotics. Odor Source Localization (OSL) deals with technologies that can allow robots to perform tasks such as detecting and navigating towards a target odor source in an unknown environment [1]. OSL has increasingly important applications including monitoring air pollution [2], locating chemical gas leaks [3], locating unexploded mines and bombs [4], and marine surveys such as finding hydrothermal vents [5], etc.

This paper focuses on the development of a robotic agent used for the robotic OSL task. This robotic agent is capable of



(a) (b)

Fig. 1. (a) Turtlebot3 waffle pi model used in this work. In addition to the onboard sensors, the robot is equipped with an anemometer for measuring wind speeds and directions; a chemical sensor for detecting odor plumes. (b) The experiment setup. The robot is initially placed at downwind area with the object of finding the odor source. A humidifier loaded with ethanol is employed to generate odor plumes, and an electrical fan is placed behind the humidifier to create an artificial wind field.

sensing odor plumes and navigating itself to the odor source autonomously in unknown environments. In this work, we use the Turtlebot3 waffle-pi as the robotic platform. The robot utilizes Robot Operating System (ROS) for operation. This robot is pre-built with a camera, 360-degree Light Detection and Ranging (LiDAR), gyroscope, accelerometer, and magnetometer for sensing the surrounding environment, and two motors for traveling in the environment. It uses Raspberry Pi 4 as the central processing unit that allows complex onboard computation and easier communication with remote computers. It uses OpenCR board (i.e., an open-source control module customized for the Turtlebot3 robot) as a powerful and customizable robot controller. The modularity of Turtlebot makes it possible to customize it with additional sensors. Additionally, ROS allows minute control over specific robot components, so that it is possible to subscribe to specific sensors and publish to navigation from the remote Personal Computer (PC). The ROS supports both Python and C++ as programming languages. Thus, existing mathematical libraries published in Python and C++ can easily be incorporated into algorithms written for the robot.

In addition to hardware and sensors, an effective navigation algorithm is required for the OSL task, which guides the robot to approach the odor source location. Like image-based navigation algorithms, which use captured images as cues to navigate a robot, olfactory-based navigation algorithms direct a robot by using detected odor plume and airflow direction/speed as cues in finding the odor source [6]. In this paper, a bio-inspired algorithm has been proposed for the OSL task, which makes the robot mimic animal odor search behaviors.

Specifically, the moth-inspired algorithm was employed in this project, which is a bio-inspired method that imitates male months mate-seeking behaviors [7]: a male moth flies upwind when detects pheromone plumes, emitted from a female moth, and moves across wind direction when plumes are absent. This behavior can be framed as a 'surge/casting' model [8], where a plume tracing robot traverses wind when missing plume contact (i.e., termed 'casting' behavior) and moves against the wind direction when detecting plumes (i.e., termed 'surge' behavior).

Contributions of this work can be summarized as 1) discuss the customization of the Turtlebot3 robot platform for odor source localization experiments; 2) find the search performance of the moth-inspired algorithm in different real-world search environments; 3) discuss possibilities of combining more sensors and machine learning based algorithms in the same robotics platform. The remainder of the paper is organized as follows. The robotic platform and experiment field are presented in Fig. 1. The Turtlebot3 robot was customized for the OSL task, the search area included an odor source with fans. The location of the odor source was unknown to the robot and changed in different experimental runs. In the remaining of this paper, Section II reviews the recent progress of olfactory-based navigation algorithms; Section III reviews technical details of the robot customization and moth-inspired navigation algorithms; Section IV presents details of performing the real-world experiments. Finally, Section V includes a discussion of including vision sensor with discussed olfactory-based sensors for the Odor Source Localization task. It also includes a discussion of the incorporation of machine learning-based methods for the OSL task.

II. Related Works

A. Olfactory-based Navigation Algorithms

The objective of olfactory-based navigation algorithms is to command robots to find odor sources relying on olfaction sensors. Like image-based navigation algorithms [9], which extract the information from images as a reference to navigate a robot, olfactory-based navigation algorithms detect odor plumes as cues to guide robots moving toward odor sources. Traditional olfactory-based navigation algorithms include the following:

1) Chemotaxis: commands the robot to trace plumes by following the odor concentration gradient [10]. A common setup is to install two chemical sensors on two sides of the robot, and the robot moves toward the side with higher chemical concentration [11], [12]. The chemotaxis method is applicable in laminar flow environments, where odor plumes disperse in a steady and spatially coherent trajectory, but in turbulent flow environments, the plume is stretched and twisted to form a patchy trajectory and an intermittent concentration gradient. Consequently, the chemotaxis method tends to be ineffective in such turbulent flow environments.

2) Bio-inspired methods: involve directing a robot to imitate olfactory behaviors observed in animals. One example of such behavior is the 'surge/casting' search strategy found in moth-inspired methods [13], [14], [15], where the robot exhibits a 'surge' behavior by moving against the wind direction when it detects odor plumes and switches to a 'casting' behavior, moving across the wind direction, when it loses contact with the plume. Lobster-inspired methods can be viewed as an enhanced version of chemotaxis. In these methods, the robot retraces its path when sensors on two sides of the robot detect the same concentration [16]. Bio-inspired methods are typically designed to be straightforward and computationally efficient during the search process. However, in turbulent flow environments, the intuitive cross-wind search strategy ('casting' behavior) may struggle to effectively guide the robot back to plume detection, resulting in longer search times and occasionally leading to search failures [17].

3) Probabilistic methods: employ mathematical and physical principles to estimate the distribution of odor plumes and predict the locations of odor sources. In these methods, the search area is divided into multiple cells, each assigned a probability representing the likelihood of containing the odor source. As the robot navigates, these probabilities are updated, eventually converging to a specific region, indicating the estimated location of the odor source. Various techniques are used to calculate these source probabilities, including Bayesian inference [18], particle filters [19], and partially observable Markov decision processes (POMDP) [20], among others. Once the source probabilities have been determined, path planning algorithms like artificial potential field (APF) [21] and A-star [22] are employed to generate search trajectories that guide the robot toward the estimated target.

These probabilistic methods provide a systematic and data-driven approach to odor source localization, allowing robots to make informed decisions based on observed data and statistical reasoning. However, the computational load of updating the source probabilities grow significantly with the increase of search area size and the number of cells inside the search area, making this type of method inapplicable to robotic agents, which have limited computational resources.

B. Robotic OSL on Ground Mobile Robots

The early attempt of applying robotic OSL algorithms on robotic agents was utilizing a ground mobile robot. For instance, Hayes *et al.* [23] utilized a group of ground mobile robots for locating the odor source location. Each robot is equipped with an odor detection sensor to measure odor concentrations at the robot position. During the search process, robots traveled in the search area, following a random walk behavior, to construct a global plume intensity map, from which the odor source location could be identified. Ryohei *et al.* [24] applied a simple moth-inspired method on a ground mobile robot. The search strategy can be summarized as a 'surge/casting' behavior pattern. A wheeled ground vehicle,

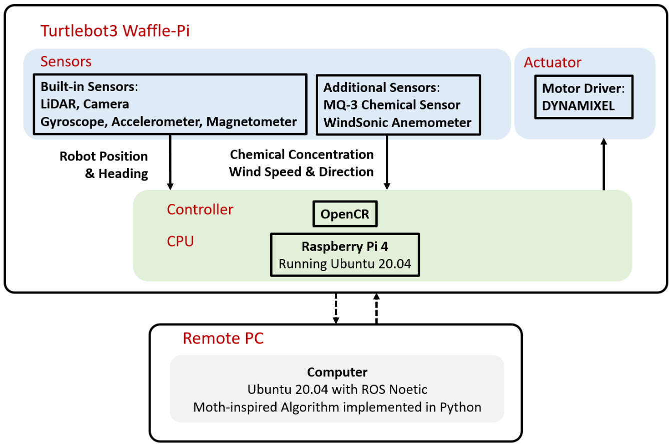


Fig. 2. System configuration. This system contains two main components, including the Turtlebot3 and the remote PC. The solid connection line represents physical connection, and the dotted connection line represents wireless link.

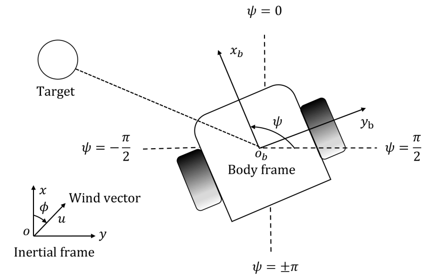


Fig. 3. Robot notations. Robot position (x, y) and heading ψ are monitored by the built-in localization system. Wind speed u and wind direction ϕ are measured from the additional anemometer in the inertial frame.

equipped with a chemical and a wind sensor, was deployed to find an odor source in a closed environment. Lochmatter *et al.* [25] also implemented the 'surge/casting' behavior pattern on a wheeled ground vehicle to find an odor source in a laminar flow environment. Ground mobile robots can also be applied to generate a 3-dimensional plume distribution map. Lu et al. [26] proposed a ground robotic agent to measure odor plume distribution at varying heights using a ground vehicle equipped with multiple gas sensors installed on a pole at different heights

Ground mobile robots are commonly employed as the search agent in the robotic OSL task. Since this robotic platform is easy to obtain and evaluate. Compared to airborne and underwater robots, ground mobile robots have the advantage of large payload, long duration, and easy recovery. Moreover, ground mobile robots can be operated in both indoor and outdoor environments without extra facility installation (e.g., a special safety net or cage is required to operate a drone in an indoor environment, and for operating AUVs, large water tanks or pools are required), making it the most flexible robotic agent to evaluate olfactory-based navigation algorithms.

III. Methodology

A. Multi-Sensory Robot Platform Development for OSL task

1) Turtlebot3 Waffle-Pi: Turtlebot3 is a popular mobile robot system for research and education. It is highly modular and customizable. It has Raspberry Pi 4 as the CPU, and the implemented system uses Ubuntu 20.04 as the Operating System of the Robot. Thus, the robot had standalone rich computation and connectivity capabilities. The onboard OpenCR controller allows the Turtlebot3 to be paired with additional sensors for increasing its functionalities. Turtlebot3's built-in sensors include Raspberry Pi Camera, 360-degree LiDAR sensor, 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer. These sensors help Turtlebot3 to measure 9-axis inertia. It also has a DYNAMIXEL diver for navigation. Turtlebot3 can perform SLAM (simultaneous localization and mapping), Navigation, and manipulation tasks with the built-in sensors.

2) Turtlebot3 Operation: Fig. 2 presents the proposed system configuration for the robotic system, which includes a robotic agent, i.e., Turtlebot3, onboard controller, and a ground station, i.e., a remote PC.

ROS Noetic was installed in the paired remote PC for controlling the robot. A local area network was used to connect the robot to the remote PC. ROS supports both Python and C++ custom programs. This means that it is possible to directly use external Python or C++ library functions in the robot. ROS allows custom programs to subscribe to specific sensors, conduct calculations, and publish (e.g., heading commands) to the robot. The sensor subscription, heading calculation with the help of external library (e.g., Pytorch) functions and heading publication can all be bundled in a single program that runs on the more powerful remote PC. The onboard Raspberry Pi's networking feature ensured low latency and reliable connectivity between the robot and the remote PC.

3) Onboard Sensor Suite: For the OSL task, additional olfactory sensors were paired with the Turtlebot3. For chemical detection, an MQ3 alcohol detector sensor was used. MQ3 sensor is a widely used Metal Oxide Semiconductor (MOS) sensor. It operates on 5V DC and consumes about 800mW. It can detect alcohol concentrations ranging from 25 to 500 ppm. The onboard anemometer (WindSonic, Gill Inc.) was used for airflow direction and wind speed measurements in the body frame.

Fig. 3 summarizes parameters measured via the onboard sensor suite, including the robot positions (x, y) and robot heading ψ in the inertial frame, chemical (odor) concentration ρ, wind speeds u, wind direction ϕ in the local frame during the plume tracing process. To convert wind direction and wind speed into the global frame, we follow the following equations:

$$\phi_{Inertial} = \phi + \psi. \tag{1}$$

All angle-related parameters are ranged from $[\pi/2, \pi/2]$. In addition, the employed chemical sensor is known with a long recovery time after a detection, i.e., the odor concentration measurement decreases to a normal value slowly. Thus, instead

Algorithm 1 Chemical Sensor Data Processing

if $\rho - \rho_{pre} > 0$ **then**
  Plume detected, $D = 1$:
else
  Plume not detected, $D = 0$:
end if
$\rho_{pre} = \rho$

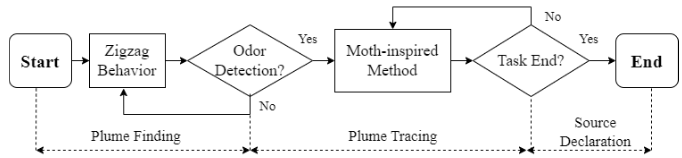


Fig. 4. The flow diagram of the proposed OSL algorithm.

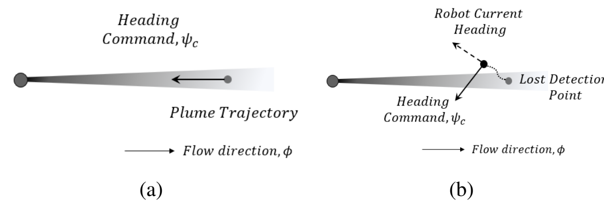


Fig. 5. The proposed moth-inspired search behaviors in the 'Plume Tracing' stage, including (a) 'Surge' behavior and (b) 'Casting' behavior.

of using a fixed concentration threshold, we utilize the gradient of odor concentration to distinguish odor detection and non-detection events, as presented in Algorithm 1. For instance, if the odor gradient is positive, i.e., $\rho - \rho_{pre} > 0$, the chemical sensor detects odor plumes; if the odor gradient is negative, i.e., $\rho - \rho_{pre} < 0$, the chemical sensor is leaving the odor plume. In Algorithm 1, D is the odor detection indicator, where $D = 0$ indicates that the robot does not detect odor plumes, and $D = 1$ represents that the robot has an odor plume detection.

The proposed olfactory-based navigation algorithm is implemented on the remote PC to process sensor observations, transmitted from the robotic agent. The algorithm calculates robot actions to guide the robot to find the odor source location. Once the robot actions are obtained, they will be transmitted back to the robot via a wireless communication link. We set the updating rate of the olfactory-based navigation algorithm at 2Hz. Moreover, to control a ground mobile robot on a 2-dimensional plane, only speed and heading commands are needed. To simplify the control problem, we assume the robot moves at a constant speed, i.e., $v_c = 0.2$ m/s, and only heading commands ψ_c are needed, which is the output from the olfactory-based navigation algorithm.

4) Search Area: The search area is a 2-dimensional space as presented in Fig. 1(b). The size of the search area is $5.5m \times 2.4m$. Inside the search area, an odor source is presented and its location is hidden to the search robot. In the experiment, we utilize non-toxic materials, i.e., ethanol, as the odor source and employ a humidifier to continuously release ethanol in the search environment. Moreover, a coordination is constructed over the search area to represent robot positions in the inertial frame i.e., $x - y$. During the search, the robot position is determined via the onboard LiDAR sensor, and $x \in [0, 5.5]$ m and $y \in [0, 2]$ m.

B. Odor Source Localization Algorithm

An OSL can be divided into three stages, including plume finding, plume tracing and source declaration [27]. Fig. 4 presents the flow-diagram of the proposed odor source localization algorithm. In the first 'Plume Finding' phase, the robot performs a 'zigzag' behavior to sense the existence of odors in the environment. If the robot detects an odor concentration surpassing a predefined threshold, the system proceeds to the 'Plume Tracing' phase, where the moth-inspired method is activated to calculate robot actions based on chemical and wind sensor readings. These robot actions will lead the robot to the odor source location. In the final 'Source Declaration' phase, the robot declares the odor source location and completes the OSL task. Moreover,

1) Plume Finding: The first stage is plume finding, which aims to detect plume in the search area. Once the robot detects plume in the search area, the plume tracing stage initiates. Here, we utilize a 'zigzag' search behavior [28] in the plume finding phase to sense the existence of odor plumes. During the 'zigzag' behavior, the robot search trajectory is dominant with the crosswind movements since the robot has a higher chance to detect odor plumes with crosswind movements than along-wind excursions, without the prior information of the odor source. Besides, we include a smaller along-wind component in the 'zigzag' behavior to ensure the exploration. During the 'zigzag' behavior, the robot travels at a constant speed, i.e., v_c, and when the robot reaches the boundaries of the search area, it turns the heading toward the inside of the search area to continue the search. The robot will switch to the plume tracing stage once the detected odor concentration is greater than a pre-defined threshold.

2) Plume Tracing: In the 'Plume Tracing' stage, we proposed a moth-inspired method to command the robot to search for the odor source. The proposed moth-inspired method [29] can be summarized as the 'surge' and 'casting' behaviors, as presented in Fig. 5.

The 'surge' behavior is activated when the robot detects odor plumes, i.e., $D = 1$. In this behavior, i.e., Algorithm 2, the robot moves upwind to progress towards the odor source location. The heading command, i.e., ψ_c, in this behavior can be computed via:

$$\psi_c = \phi_{Inertial} + 180. \tag{2}$$

If the robot moves out of plumes, it will activate the 'casting' behavior, i.e., Algorithm 3, to move cross-wind until it finds plumes again. During this behavior, the robot uses the equation 3 to calculate the target heading ψ_c.

$$\psi_c = \phi_{Inertial} + 90. \tag{3}$$

Algorithm 2 'Surge' Behavior

if Behavior is 'Surge' **then**
  $\psi_c = \phi_{Inertial} + 180$
  if Plume not detected, $D == 0$ **then**
    return 'Track-out' Behavior
  end if
end if

Algorithm 3 'Casting' Behavior

if Behavior is 'Casting' **then**
  $\psi_c = \phi_{Inertial} + 90$
  if Plume is detected, $D == 1$ **then**
    return 'Surge' Behavior
  else
    return 'Casting' Behavior
  end if
end if

Once the robot re-detect odor plumes, it switches back to the 'surge' behavior to continue the upwind movement. These two search behaviors are alternated in the 'Plume Tracing' phase until the robot finds the odor source.

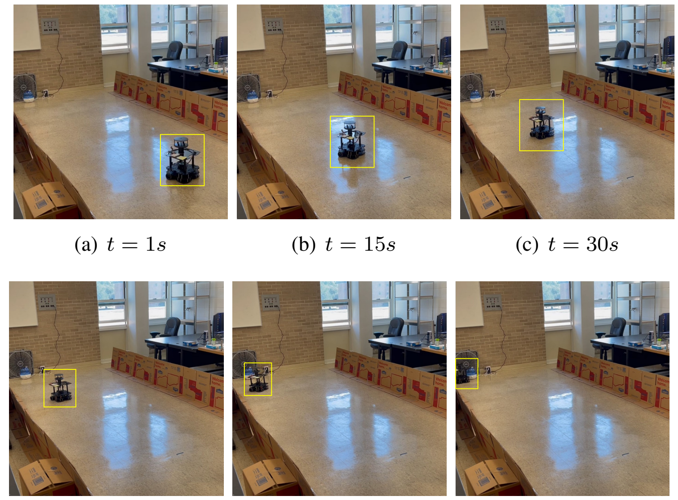
3) Source Declaration: In this work, the robot is considered as successfully found the odor source if the robot position is within 0.5 m of the odor source location. In the future, we are planning to use a camera in the source declaration phase and add a vision processing module to automatically declare the odor source location.

IV. Experiments

A. Experiment Setup

Experiments were conducted in the Automatic Control Lab at the Louisiana Tech University. The lab area was divided into a search area where the robot can navigate and an operation area for the remote PC. The size of the search area is 5.5×2.4 m^2. The robot, odor and airflow source were randomly placed in this search area for each trial run. Ethanol vapor was employed as the odor source as it is commonly implemented in OSL research [30]. A humidifier was used to disperse ethanol vapor consistently as the odor plume. An electric fan was used behind the humidifier to increase odor propagation. Before the experiment, a map of the search area is created with Turtlebot3's Simultaneous Localization and Mapping (SLAM). The robot maps the area, obstacle and boundaries of the search area using the 360-degree LiDAR sensor. Turtlebot3 uses both odometry and LiDAR scan data to calculate its position and rotation in reference to the map coordinate system.

During an experiment run, the robot sends sensor measurements to the remote PC. The remote PC runs the moth-inspired navigation algorithm to calculate robot's heading command and transmit it back to the robot. The robot follows the heading command to move to a new location inside the search area and repeats the above process until it finds the odor source location, i.e., the robot gets within 0.5m (this threshold is determined based on the search area and robot dimensions) of the odor source.



(a) $t = 1s$ (b) $t = 15s$ (c) $t = 30s$

(d) $t = 45s$ (e) $t = 60s$ (f) $t = 76s$

Fig. 6. Snapshots of an OSL test with the moth-inspired method. The robot position is highlighted with the a yellow rectangle, and the robot correctly finds the odor source at 76 s.

B. Search Results

Fig. 6 depicts Turtlebot's OSL navigation based on the moth-inspired method. At the start of the search ($t = 1$ s), the robot senses odor detection and switches to the 'Plume tracing' stage to trace the odor source location. In this stage, the robot employed the 'surge' behavior to move against the wind direction to approach the odor source location (from $t = 1$ s to $t = 15$ s). Then, the robot lost the plume contact at $t = 17$ s and switched to the 'casting' behavior to detect plumes in crosswind movements. At $t = 30$ s, it reacquired the odor plumes and switched back to the 'surge' behavior to move against the wind direction. At $t = 45$ s, the robot moves close to the odor source location and remains in the 'surge' behavior until it finds the odor source at $t = 76$ s. The video of this trial can be found at [1].

V. Conclusion and Future Work

This paper presents a robotic system developed for the robotic OSL task. A Turtlebot3 robot was employed as the platform and was installed with a comprehensive sensor suite to sense its position, airflow speed and direction, and chemical concentration at its location. In the proposed robotic system, sensory observations captured from the robotic agent will be transmitted back to a ground station to calculate robot actions. Once the robot actions are obtained, they will be sent back to the robot and command the robot to move to a new position. This process is repeated until the robot finds the odor source location. Through a robotic OSL trial, we verify the effectiveness of the proposed robotic system in finding an odor source in unknown environments. Moreover, the search

[1]Experiment video link: https://youtu.be/726iJKpz1Ic

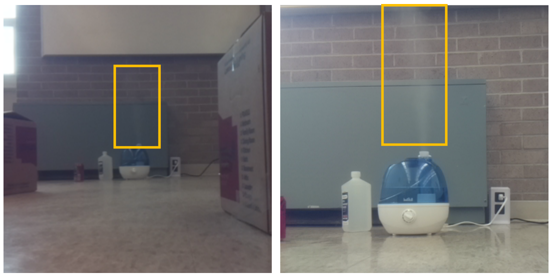


Fig. 7. (a) Picture of odor plumes captured from Turtlebot3 waffle pi's camera from a distance. (b) Picture of odor plumes captured from Turtlebot3 waffle pi's camera from close.

results show that the proposed moth-inspired algorithm can successfully navigate a ground mobile robot to the odor source location in a lab environment.

Turtlebot3 can take pictures and record video with the built-in Raspberry Pi Camera. Fig. 7 shows photos captured with Turtlebot3. The future scope of the robot platform includes the incorporation of vision sensor for OSL task. Olfactory-based algorithms can perform well in laminar airflow environments. But in turbulent airflow environment, erratic airflow direction and chemical detection reading can disrupt steady navigation. Computer vision can be an effective addition to existing olfactory sensing in turbulent airflow environments. With the recent success of machine learning techniques, deep learning models, such as convolutional neural networks (CNNs) are commonly used for processing images and detecting objects automatically [31]. One direction of our future work is to utilize a pre-trained vision model, such as the YOLO series [32], to process images captured from the mobile robot to extract odor source information and integrate it with olfactory observations from chemical and wind sensors. The combination of computer vision and robotic olfaction provides a more comprehensive observation of the environment, enabling the robot to interact with the environment in more ways and enhancing the navigation performance.

The future scope of this robot platform also includes using machine learning to calculate the robot's target heading. Reinforcement learning (RL) method can be used for olfactory-based navigation in robots [17]. In RL-based method, the robot is a plume-tracing agent and the search area is the outside environment, and the robot is rewarded as it chooses actions that benefit in finding the odor source [17]. Alternatively, supervised learning methods, including using a feedforward (FNN) and a long short-term memory neural network (LSTM) can be used for OSL tasks [33]. The ROS platform used in Turtlebot3 allows efficient packaging of machine learning based libraries in a single Python or C++ program. The future scope of this platform includes incorporating computer vision and machine learning based target heading calculation for OSL tasks, and comparing the solution with bio-inspired methods.

References

[1] G. Kowadlo and R. A. Russell, "Robot odor localization: a taxonomy and survey," *The International Journal of Robotics Research*, vol. 27, no. 8, pp. 869–894, 2008.

[2] M. Dunbabin and L. Marques, "Robots for environmental monitoring: Significant advancements and applications," *IEEE Robotics & Automation Magazine*, vol. 19, no. 1, pp. 24–39, 2012.

[3] S. Soldan, G. Bonow, and A. Kroll, "Robogasinspector-a mobile robotic system for remote leak sensing and localization in large industrial environments: Overview and first results," *IFAC Proceedings Volumes*, vol. 45, no. 8, pp. 33–38, 2012.

[4] R. A. Russell, "Robotic location of underground chemical sources," *Robotica*, vol. 22, no. 1, pp. 109–115, 2004.

[5] G. Ferri, M. V. Jakuba, and D. R. Yoerger, "A novel method for hydrothermal vents prospecting using an autonomous underwater robot," in *2008 IEEE International Conference on Robotics and Automation*. IEEE, 2008, pp. 1055–1060.

[6] J. A. Farrell, J. Murlis, X. Long, W. Li, and R. T. Cardé, "Filament-based atmospheric dispersion model to achieve short time-scale structure of odor plumes," *Environmental fluid mechanics*, vol. 2, no. 1-2, pp. 143–169, 2002.

[7] R. T. Cardé and A. Mafra-Neto, "Mechanisms of flight of male moths to pheromone," in *Insect pheromone research*. Springer, 1997, pp. 275–290.

[8] L. L. López, V. Vouloutsi, A. E. Chimeno, E. Marcos, S. B. i Badia, Z. Mathews, P. F. Verschure, A. Ziyatdinov, and A. P. i Lluna, "Moth-like chemo-source localization and classification on an indoor autonomous robot," in *On Biomimetics*. IntechOpen, 2011.

[9] G. Chaurasia, S. Duchene, O. Sorkine-Hornung, and G. Drettakis, "Depth synthesis and local warps for plausible image-based navigation," *ACM Transactions on Graphics (TOG)*, vol. 32, no. 3, pp. 1–12, 2013.

[10] H. Ishida, K.-i. Suetsugu, T. Nakamoto, and T. Moriizumi, "Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors," *Sensors and Actuators A: Physical*, vol. 45, no. 2, pp. 153–157, 1994.

[11] H. Ishida, G. Nakayama, T. Nakamoto, and T. Moriizumi, "Controlling a gas/odor plume-tracking robot based on transient responses of gas sensors," *IEEE Sensors Journal*, vol. 5, no. 3, pp. 537–545, 2005.

[12] A. Lilienthal and T. Duckett, "Experimental analysis of gas-sensitive Braitenberg vehicles," *Advanced Robotics*, vol. 18, no. 8, pp. 817–834, 2004.

[13] W. Li, J. A. Farrell, S. Pang, and R. M. Arrieta, "Moth-inspired chemical plume tracing on an autonomous underwater vehicle," *IEEE Transactions on Robotics*, vol. 22, no. 2, pp. 292–307, 2006.

[14] S. Shigaki, S. Haigo, C. H. Reyes, T. Sakurai, R. Kanzaki, D. Kurabayashi, and H. Sezutsu, "Analysis of the role of wind information for efficient chemical plume tracing based on optogenetic silkworm moth behavior," *Bioinspiration & biomimetics*, vol. 14, no. 4, p. 046006, 2019.

[15] A. M. Matheson, A. J. Lanz, A. M. Medina, A. M. Licata, T. A. Currier, M. H. Syed, and K. I. Nagel, "A neural circuit for wind-guided olfactory navigation," *Nature Communications*, vol. 13, no. 1, p. 4613, 2022.

[16] B. T. Michaelis, K. W. Leathers, Y. V. Bobkov, B. W. Ache, J. C. Principe, R. Baharloo, I. M. Park, and M. A. Reidenbach, "Odor tracking in aquatic organisms: the importance of temporal and spatial intermittency of the turbulent plume," *Scientific reports*, vol. 10, no. 1, p. 7961, 2020.

[17] L. Wang, S. Pang, and J. Li, "Olfactory-based navigation via model-based reinforcement learning and fuzzy inference methods," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 10, pp. 3014–3027, 2021.

[18] S. Pang and J. A. Farrell, "Chemical plume source localization," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 36, no. 5, pp. 1068–1080, 2006.

[19] J. Li, Q. Meng, Y. Wang, and M. Zeng, "Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm," *Autonomous Robots*, vol. 30, no. 3, pp. 281–292, 2011.

[20] H. Jiu, Y. Chen, W. Deng, and S. Pang, "Underwater chemical plume tracing based on partially observable markov decision process," *International Journal of Advanced Robotic Systems*, vol. 16, no. 2, p. 1729881419831874, 2019.

[21] S. Pang and F. Zhu, "Reactive planning for olfactory-based mobile robots," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2009, pp. 4375–4380.

[22] L. Wang and S. Pang, "Chemical plume tracing using an auv based on pomdp source mapping and a-star path planning," in *OCEANS 2019 MTS/IEEE SEATTLE*. IEEE, 2019, pp. 1–7.

[23] A. T. Hayes, A. Martinoli, and R. M. Goodman, "Distributed odor source localization," *IEEE Sensors Journal*, vol. 2, no. 3, pp. 260–271, 2002.

[24] R. Kanzaki, N. Sugi, and T. Shibuya, "Self-generated zigzag turning of Bombyx mori males during pheromone-mediated upwind walking (Physology)," *Zoological science*, vol. 9, no. 3, pp. 515–527, 1992.

[25] T. Lochmatter, X. Raemy, L. Matthey, S. Indra, and A. Martinoli, "A comparison of casting and spiraling algorithms for odor source localization in laminar flow," in *2008 IEEE International Conference on Robotics and Automation*. IEEE, 2008, pp. 1138–1143.

[26] L. Osório, G. Cabrita, and L. Marques, "Mobile robot odor plume tracking using three dimensional information." in *ECMR*, 2011, pp. 165–170.

[27] W. Naeem, R. Sutton, and J. Chudley, "Chemical plume tracing and odour source localisation by autonomous vehicles," *The Journal of Navigation*, vol. 60, no. 2, pp. 173–190, 2007.

[28] L. Wang and S. Pang, "Robotic odor source localization via adaptive bio-inspired navigation using fuzzy inference methods," *Robotics and Autonomous Systems*, vol. 147, p. 103914, 2022.

[29] J. A. Farrell, S. Pang, and W. Li, "Chemical plume tracing via an autonomous underwater vehicle," *IEEE Journal of Oceanic Engineering*, vol. 30, no. 2, pp. 428–442, 2005.

[30] Q. Feng, H. Cai, Z. Chen, Y. Yang, J. Lu, F. Li, J. Xu, and X. Li, "Experimental study on a comprehensive particle swarm optimization method for locating contaminant sources in dynamic indoor environments with mechanical ventilation," *Energy and buildings*, vol. 196, pp. 145–156, 2019.

[31] S. Frizzi, R. Kaabi, M. Bouchouicha, J.-M. Ginoux, E. Moreau, and F. Fnaiech, "Convolutional neural network for video fire and smoke detection," in *IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2016, pp. 877–882.

[32] W. S. M. Rafik Ghali, Moulay A. Akhloufi, "Deep learning and transformer approaches for uav-based wildfire detection and segmentation," *Deep Learning Methods for Remote Sensing*, 2022.

[33] L. Wang, Z. Yin, and S. Pang, "Learn to trace odors: Robotic odor source localization via deep learning methods with real-world experiments," in *SoutheastCon 2023*. IEEE, 2023, pp. 524–531.