Olfactory Arm Mobile Robot for Object Inspection Based on Fuzzy Logic and Support Vector Machine

To cite this article: Rendyansyah et al 2019 J. Phys.: Conf. Ser. 1196 012019

View the article online for updates and enhancements.
Olfactory Arm Mobile Robot for Object Inspection Based on Fuzzy Logic and Support Vector Machine

Rendyansyah 1, Muhammad Rivai 2, Djoko Purwanto 3

1Department of Computer Engineering, University of Sriwijaya, Palembang, Indonesia
2,3Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia.

*corresponding author’s e-mail : rendyansyah@ilkom.unsri.ac.id

Abstract. In recent years, there have been suspicious objects containing chemical materials intentionally placed on roads, fields and parking lots. The objects are considered harmful to be examined. Therefore, we need tools that can replace people in checking the dangerous objects. Robot is considered as a technology that can be applied to handle it. This study has designed a mobile robot system equipped with robotic arm and electronic nose to inspect the suspected object. The robotic arm is used to bring the electronic nose closer to the object's surface. This robot can find the source of gas and surround the object with a distance of 20 cm. The movement of the mobile robot and robotic arm is controlled using fuzzy logic. The Support Vector Machine method is used to identify gas types. This olfactory arm mobile robot can find a gas source and recognize the type of gas with a success rate of 92%.

1. Introduction.

There are several aspects of the human being unable to carry out tasks due to distance, physical limitations, dangerous conditions, and complicated situations. In recent years, Molotov bombs, a type of gasoline in a bottle tied with cables and batteries, and objects such as gas cylinders of liquefied petroleum gas (LPG) wrapped in plastic have been found in the public environment. The object is placed intentionally which can cause public discomfort. People do not want to take the risk to approach the objects. Therefore, we need a system that can examine the object whether it contains hazardous materials. In today's world, robotic systems are used to help human works. One of the jobs that are often done by robots is to investigate areas or objects that are thought to be dangerous [1]. Operators can check the suspected objects without having to approach them directly which can avoid the dangerous situations.

Researches on olfactory robots have been carried out in detecting the gas contained in objects or area [2] [3], [4]. Other studies have developed mobile robots accompanied by intelligence methods to detect gas [5], to declare sources [6], to localize [7], [8], and to identify gases, [9]. Therefore, the olfactory mobile robot is the interesting topics in this study used to inspect an object. The gas sensor or electronic nose located on the mobile robot is used to detect and recognize the type of gas. To recognize the type of gas can use a classification technique based on the pattern produced by the electronic nose. One method used for the pattern recognition is Support Vector Machine (SVM) [10]. This method can recognize linear and non-linear data patterns [11], [12] and is feasible to be applied to the electronic noses in the mobile robot applications. Usually, the gas sensor is located in front, left, or right of the
mobile robot [13], however, this has not provided accurate information. Therefore, we need a way to get the electronic nose closer to the target so that it can detect the type of gas accurately. Some researchers propose a robotic arm to be closer to the desired target [14], [15], however, the movement is still controlled manually. Therefore, it is necessary to design an automatic movement of a robotic arm equipped with gas sensors integrated in a mobile robot. When a user knows the position of a suspected object, this robot is controlled manually to the target using wireless communication. However, when the robot is close to the target, automatic movement is activated to investigate by surrounding the object. Conventional control systems in mobile robots and robotic arms often involve complex mathematical calculations. On the other hand, artificial intelligence techniques such as fuzzy logic control are easy in design, because they mimic the logic of an expert without requiring a mathematical model of the system [16], [17]. Fuzzy logic controls are known as Mamdani and Sugeno models [18], [19]. The Mamdani model requires careful calculation which results in a slower control system. While Sugeno involves simple calculations that can be applied to a low-memory microcontroller. In this study, we use fuzzy logic control with the Sugeno model as a robotic arm and mobile robot navigations. While the pattern recognition technique of the SVM is applied in an electronic nose to identify the gas types.

2. Methods
2.1. Olfactory Arm Mobile Robot.

The olfactory arm mobile robot is a mobile robot equipped with an electronic nose and robotic arm that can detect and recognize the gas types. The gas is detected using four commercial semiconductor gas sensors of TGS2600 placed at the end of the robotic arm. An electronic nose system consisting of MQ2, MQ4, and MQ135 gas sensors is used to identify the gas types. Figure 1 shows the mobile robot used in this experiments. This robot consists of proximity sensors, electronic nose, motor driver, and wireless communication. The block diagram of the hardware of this system is shown in Figure 2. The controller I is used to receive data from a proximity sensor which is then processed by fuzzy logic to control the movement of the mobile robot. The controller II receives data from the TGS2600 gas sensor which is also processed by fuzzy logic to drive the servo motor on the robotic arm in detecting gas. This controller also receives data from three gas sensors that are converted to digital data to be sent to the computer via wireless communication. The computer receives this gas sensor data which is then processed by the SVM in recognizing the type of gas after the training phase.

Figure 1. The olfactory arm mobile robot at the: (a) side (b) front views.
2.2. Fuzzy Logic Controller.

A fuzzy logic theory is inspired by a person's ability to take action based on information from his experience [17]. Fuzzy logic works based on linguistic rules of reasoning and decision making on uncertain information. This rule is designed by experienced people to control the automatic systems [16]. Fuzzy logic is implemented on both controller 1 for the mobile robot movements and controller 2 for the robotic arm movements. Figure 3 shows the block diagram of the fuzzy logic control for the mobile robot, while Figure 4 shows the block diagram of the fuzzy logic control for the robotic arm.

![Figure 2. The block diagram of the olfactory arm mobile robot.](image)

![Figure 3. The fuzzy logic control for movements of the mobile robot for: (a) left, and (b) right sides.](image)
2.3. Support Vector Machine Technique.

One of the most interesting methods in the pattern recognition field is the SVM [10]. The SVM is learning based on statistical theory combined with existing learning theories such as kernel concepts, general theory, optimization methods, and others [4]. The SVM can classify data linearly or non-linearly, where this technique always tries to find the best separating hyperplane according to the specified class [11], [12]. One example of a hyperplane for the case of two classes is shown in Figure 5. The optimal hyperplane can be converted to a quadratic programming form which is then converted into a double form, expressed in Eq. (1).

\[
\begin{align*}
\max_{\alpha} & \sum_{k=1}^{l} \alpha_k - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\
\text{Subject to:} & \sum_{i=1}^{l} \alpha_i y_i = 0 \\
& 0 \leq \alpha_i \leq C, \ i = 1, \ldots, l
\end{align*}
\]

Figure 5. Hyperplane for the two classes in (a) linear, and (b) non-linear cases [11].
In the non-linear case, the function $k(x_i, x_j)$ is solved by utilizing kernel functions such as polynomial, Gaussian, radial basis function, and multi-layer perceptron [10], [11]. On the other hand, the SVM learning algorithm uses the SVM sequential method for the classification process [20]. This algorithm will generate an optimal Lagrange value for the classified data, in which the data was previously modified to form a higher dimensional feature using kernel function. The one-against-the others SVM architecture used in the electronic nose is shown in Figure 6.

3. Experiment Results
The experiment aims to determine the movements of the robot simultaneously in examining an object containing gasoline or butane gas. The robotic arm only moves vertically, while the horizontal movement is assisted by the mobile robot surrounding the object's wall. The experimental set-up of the olfactory arm mobile robot for object inspection is shown in Figure 7. The gas sensor patterns for gasoline and butane gas is shown in Figure 8.
Figure 8. The gas sensor patterns of (a) gasoline and (b) butane gas.

In this experiment, the mobile robot is on the right side of the object containing gasoline. The mobile robot runs until the object distance is less than 50 cm. Fuzzy logic control is then activated to maintain the position of the robot as far as 20 cm to the object. The response of the proximity sensor and gas sensor is shown in Figure 9. The robot reaches the object at 1.1 seconds. The robot stops at 8.8 seconds which indicates that robotic arm detects gas. Fuzzy logic control on the robotic arm is then activated to find a larger concentration of gas which is at 11.0 seconds. Meanwhile, Figure 10 shows the response of the proximity sensor and gas sensor when the robot is on the left side of the object. The responses of the sensors when the robot is on the right side, and the left side of the object containing butane gas are shown in Figure 11, and Figure 12, respectively.

The next experiment aims to determine the ability of the olfactory arm mobile robot to find the gas source and identify the gas types. This experiment was carried out 25 times, in which the object is contained gasoline and butane gas alternately. The results of this experiment are shown in Table 1. The robot can find the gas source and is able to recognize the gas type contained in the object with a success rate of 92%.

Figure 9. The mobile robot is on the right side of the object containing gasoline: (a) the proximity sensor, and (b) the gas sensor.

Figure 10. The mobile robot is on the left side of the object containing gasoline: (a) the proximity sensor, and (b) the gas sensor.
Figure 11. The mobile robot is on the right side of the object containing butane gas: (a) the proximity sensor, and (b) the gas sensor.

Figure 12. The mobile robot is on the left side of the object containing butane gas: (a) the proximity sensor, and (b) the gas sensor.

Table 1. The ability of the olfactory arm mobile robot to find the gas source and identify the gas types.

| No. | Movement | Gas     | Target | Recognition |
|-----|----------|---------|--------|-------------|
| 1   | Right    | Gasoline| Gasoline| Success     |
| 2   | Right    | Gasoline| Gasoline| Success     |
| 3   | Right    | Gasoline| Gasoline| Success     |
| 4   | Right    | Gasoline| Gasoline| Success     |
| 5   | Right    | Gasoline| Gasoline| Success     |
| 6   | Right    | Gasoline| Gasoline| Success     |
| 7   | Left     | Gasoline| Gasoline| Success     |
| 8   | Left     | Gasoline| Gasoline| Success     |
| 9   | Left     | Gasoline| Gasoline| Success     |
| 10  | Left     | Gasoline| Gasoline| Success     |
| 11  | Left     | Gasoline| Gasoline| Success     |
| 12  | Left     | Gasoline| Gasoline| Success     |
| 13  | Right    | Butane  | Butane  | Success     |
| 14  | Right    | Butane  | Butane  | Success     |
| 15  | Right    | Butane  | Butane  | Success     |
| 16  | Right    | Butane  | Gasoline| Failed      |
| 17  | Right    | Butane  | Butane  | Success     |
| 18  | Right    | Butane  | Butane  | Success     |
| 19  | Left     | Butane  | Butane  | Success     |
| 20  | Left     | Butane  | Butane  | Success     |
| 21  | Left     | Butane  | Butane  | Success     |
| 22  | Left     | Butane  | Gasoline| Failed      |
| 23  | Left     | Butane  | Butane  | Success     |
| 24  | Left     | Butane  | Butane  | Success     |
| 25  | Right    | Butane  | Butane  | Success     |
4. Conclusion.
This study has developed a robot consisting of a mobile robot and robotic arm equipped with proximity sensors, and an electronic nose to inspect an object containing gas. The electronic nose system composes of a semiconductor gas sensor array and a SVM pattern recognition algorithm to identify the gas types. Fuzzy logic control is used for the movement of the mobile robot and the robotic arm to find gas sources accurately. The robot approaches and examines object containing gasoline and butane from left and right sides alternately in the laboratory room. The experimental results show that this robot can find the source of gas and surround the object with a distance of 20 cm. The robotic arm can search for a gas source at its highest concentration. Overall, this olfactory arm mobile robot can find a gas source and recognize the type of gas with a success rate of 92%. For future works, this robot will be developed to find dangerous gas leaks in the open air, where the wind will be an inhibiting factor for the robot to find the target.

Acknowledgment
This Research was carried out with financial aid support from the Ministry of Research, Technology and Higher Education of the Republic of Indonesia (Kemenristekdikti RI).

References
[1] E.S. Redden, R.A. Pettitt, C.B. Cartens, and L.R. Elliot, “Scalability of Robotic Displays: Display Size Investigation,” Human Research and Engineering Directorate, Army Research Laboratory, May 2008.
[2] M. Rivai, Rendyansyah, D. Purwanto, “Implementation of Fuzzy Logic Control in Robot Arm for Searching Location of Gas Leak”, International Seminar on Intelligent Technology and Its Application, pp. 69-74, 2015.
[3] R. Watiasih, M. Rivai, R.A. Wibowo, and O. Penangsang, “Path Planning Mobile Robot Using Waypoint for Gas Level Mapping”, International Seminar on Intelligent Technology and Its Application, pp. 244-249, 2017.
[4] P. Jiang, M. Zeng, Q. Meng, F. Li, and Y. Li, “A Novel Object Recognition Method for Mobile Robot Localizing a Single Odor/Gas Source in Complex Environments”, Robotics, Automation and Mechatronics, IEEE Conference, pp. 1-5, 2008.
[5] D. Martínez, J. Moreno, M. Tresanchez, M. Teixido, D. Font, A. Pardo, S. Marco, and J. Palacín, “Experimental Application of an Autonomous Mobile robot for Gas Leak Detection in Indoor Environments”, Information Fusion (FUSION), International Conference, pp. 1-6, 2014.
[6] J. Li, Q. Meng, Y. Wang, and M. Zeng, “Single Odor Source Declaration in Outdoor Time-variant Airflow Environment”, Robotics and Biomimetics (ROBIO), IEEE International Conference, pp. 143-148, 2010.
[7] G.A. Rahardi, M. Rivai, D. Purwanto, “Implementation of Hot-Wire Anemometer on Olfactory Mobile Robot to Localize Gas Source”, International Conference on Information and Communications Technology, pp. 412-417, 2018.
[8] P. Jiang, X. Hong, dan A. Ge, “Mobile Robot Gas Source Localization Based on Behavior Strategies”, Proceedings of the 33rd Chinese Control Conference, pp. 8304-8308, 2014.
[9] M. Trincavelli and A. Loutfy, “Feature Selection for Gas Identification With a Mobile robot”, Robotics and Automation (ICRA), 2010 IEEE International Conference, pp. 2852-2857, 2010.
[10] H. Byun, and S.W. Lee, “A Survey on Pattern Recognition Applications of Support Vector Machines”, International Journal of Pattern Recognition and Artificial Intelligence, Vol. 17, No. 3, pp. 459-486, 2003.
[11] C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition”, Data Mining and Knowledge Discovery, pp. 121-167, 1998.
[12] X. Wang, H.R. Zhang dan C.J. Zhang, “Signal Recognition of Electronic Nose Based on Support Vector Machines”, Proceeding of the Fourth International Conference on Machine Learning and Cybernetics, pp. 3394-3398, 2005.

[13] H. Ishida, T. Ushiku, and S. Toyama, “Mobile Robot Path Planning Using Vision and Olfaction to Search for a Gas Source”, Sensors, pp. 1112-1115, 2005.

[14] V.J. Gohil, S.D. Bhagwat, A.P. Raut, and P.R. Nirmal, “Robotics Arm Control Haptic Technology”, International Journal of Latest Research in Science and Technology, Vol. 2, Issue 2, pp. 98-102, 2013.

[15] V. Ramya, B. Palaniappan, and T. Akilan, “Embedded System for Robotic Arm Movement Control Using Web Server and Zigbee Communication”, International Journal of Computer Applications, Proceedings, pp. 30-34, 2013.

[16] A. Fatmi, A.A. Yahmadi, L. Khriji, and N. Masmoudi, “A Fuzzy Logic Based Navigation of a Mobile Robot”, World Academy of Science, Engineering and Technology, pp. 169-174, 2006.

[17] S. El-Teleity, Z.B. Nossair, H.M.A.K. Mansour, dan A. TagElDein, “Fuzzy Logic Control of an Autonomous Mobile Robot”, Methods and Models in Automation and Robotics, International Conference, pp. 188-193, 2011.

[18] Fahmizal dan C.H. Kuo, “Development of a Fuzzy Logic Wall Following Controller for Steering Mobile Robots”, International Conference on Fuzzy Theory and Its Application, pp. 7-12, 2013.

[19] U. Farooq, A. Khalid, M. Amar, A. Habiba, S. Shafique, dan R. Noor, “Design and Low Cost Implementation of a Fuzzy Logic Controller for Wall Following Behavior of a Mobile Robot”, International Conference on Signal Processing Systems, pp. 740-746, 2010.

[20] S. Vijayakumar, dan S. Wu, “Sequential Support Vector Classifiers and Regression”, Proc. International Conference on Soft Computing (SOCO’99), pp. 610-619, 1999.