Optimal Gas Sensors Arrangement in Odor Searching Robot

By 17_NLH

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[1]Nyayu Latifah Husni, [2]Ade Silvia
Electrical Engineering
Politeknik Negeri Sriwijaya
Palembang, Indonesia
[1]nyayu_latifah@polsri.ac.id,
[2]ade_silvia@polsri.ac.id

[3]Siti Nurmaini
Intelligent System Research Group
Faculty of Computer Science
Universitas Sriwijaya
Palembang, Indonesia
[3]siti_nurmaini@unsri.ac.id

[4]Irsyadi Yani
Mechanical Engineering Department
Faculty of Engineering
Universitas Sriwijaya
Palembang, Indonesia
[4]yani_irs@yahoo.com

***Abstract*— This paper presents an analysis of an optimal sensor arrangement in Odor Searching Robot (OSR). 5 gas sensors integrated in OSR can help the OSR to navigate to the source. Since low cost, low computation and robust robot is preferred in swarm robot application, the OSR, as an individual robot of swarm in this study, is designed to be able to switch into the mode 3 or the mode 5 in order to analyze the optimal distance of the gas sensors arrangement that can be integrated in the OSR. By knowing the optimal sensor arrangement, the low cost and or the low computation OSR can be established. Algorithms of fuzzy logic for 3 and 5 gas sensors are tested in open environment. The concentration of gas is used as the input of the fuzzy logic. The robot uses the concentration, as its parameters in determining which way that it should take. From this research, it can be concluded that there was no significant difference between using 3 gas sensors or 5 gas sensors.**

Keywords—fuzzy logic, gas sensor, mobile robot, navigation.

I. INTRODUCTION

To find odor source in uncertain environment became one of the most interesting robotic research [1]. Some strategies were developed in order to localize the odor source more quickly and easily [2]–[9]. In navigating to the source, the mobile robot should be able to avoid the obstacles and to follow the target with minimal time consumption. However, this condition could not be achieved easily. The output of the previous odor searching research experiments still showed some drawsbacks, namely: i. the research cannot be implemented in real situation. Some of the robots were tested using very scalable areas with so many limitations and conditions [1], [10]–[12]; ii. the robot used in the research needed more cost and more computation. One of the examples is research that implement the probabilistic approach [13]–[17]. This research used a map to reduce the uncertainty of the task. The map, of course, can reduce the uncertainty occurred in the searching task and can lead the robot to the odor source. However, the complexity of algorithm computation will increase. This will cause the enhancement of the size, cost, and the movement of the Odor Searching Robot (OSR).

To overcome the drawback of computation, some research still kept on developing various basic approaches, such as: i. gradient ascent, ii. Bio inspired, and iii. Probabilistic inference [18]. The gradients ascent depended on the wind direction. Biased Random Walk was one of the examples of gradient ascent approach. It was simple and easy to be implemented, however, it had bad performance [18]. Bio inspired in general imitated the behavior of animal, such as male moth and leaf-eating insects that relied on the female pheromone and plant scent respectively. However, this approach was inefficient, inaccurate, and It really depended on the wind [19]. In infotaxis approach, Moraud [20] stated that to enhance the capability of robot in finding the odor source a probabilistic approach was needed. It worked using exploiring and exploiting strategies. Exploiring in this approach has purpose to collect environmental information, while exploiting intended to analyze the information obtained during the exploration and moved the odor searching robot to target location based on that information [20]. This algorithm allowed the peaky structure of the odor plume to be transfered to smoother function [18] to make easy the calculation of probability distribution. However, this algorithm was implemented only in simulation.

When implementing the robot in real experiment that especially relates to the plume of the the source, some difficulties usually occurred, namely: i) the concentration of the plume sensed normally would not be the same with the surrounding. The environment uncertainty sometimes broke the odor into some different concentrations. Normally, where no disturbance, the high concentration of odor can be sensed near the source, however, this condition cannot be achieved in the environment with high uncertainties, where wind or other substances may occur in that place. ii) the gas was not always in continuous one, except in the form of random pieces of concentration. In general, the OSR only received infrequent signal and patchy information, however, they should be able to track and navigate to the source. They might surge upwind when they received an indication of the existing of odor plume. When they lost contact with it, they could cast cross-wind. However, these strategies are only effective in dense conditions, i.e., close to the source where the odor plume can be considered as a continuous cloud [21].

In this research, a fuzzy logic for 3 and 5 gas sensor was proposed as the controller of the OSR. An integration of intelligences to the robots will give advantages for OSR performance. By complementing intelligences to the OSR, they will have an ability to decide which way should be followed, relying on their intellective capability [22]. This research has purposes to analyze the optimal gas sensor arrangement in order to achieve the robustness of the individual robot and to analyze the possibility of decreasing the number of gas sensors that should be used in the system. Basically, using more number of sensors, of course, will increase the price and also the number of computation. This research has an aim to analyze whether this additional gas sensors is really needed or not. Therefore, a comparison between 3 and 5 gas sensors arrangement was analyzed. In uncertain environment, at the beginning of odor searching, there is no information about the odor concentration. The OSR in this study will itinerate in order to make connection to the odor plume. When they have connected to the odor, they would activate their gas sensors and the fuzzy logic would work based on the gas sensors data. The 3 and 5 gas sensors were introduced to the robots. Each of their performance than was analyzed in this paper.

II. APPROACHES IN ODOR SEARCHING ROBOT

Recently, some of research in OSR have been conducted in various of applications. Kowadlo and Russel [23], Ishida [10] and Thomas Lochmatter [12] described the detail work in these research. G. Kowadlo and R.A. Russell provided the odor localization approaches in a Venn diagram [23]. The OSR approaches were divided into 3 categories: 1. Early work, 2. Reactive Gradient Climbing, and 3. Turbulence Dominated Fluid Flow.

According to Ali Marjovi [24], previous works has proposed many approaches implementing in OSR, such as: Chemotaxis (concentration gradient climbing) [25], [26], [27], anemotaxis [28], [29], BESA (biasing expansion swarm approaches) [30], BRW (biased random walk) [31], Particle Swarm Optimization [32], Modified PSO [33], Learning PSO [34], Niching PSO [35], Glow-Worm Swarm Optimization (GSO) [36], [37], [38]. Most of these studies made assumption that the robots started their search near or within the plume or in other word the robots only tracked the odor to the source.

This research focused on fuzzy algorithm. Fuzzy logic is very useful in many areas of odor localization applications. It can be used as the network controller and input sensors information processor. In this research, the information from the TGS sensors was collected and processed using fuzzy algorithm. After fuzzification, fuzzy inferencing, and defuzzification process, the PWM of the robots can be controlled in such a way so that it can reach the odor source as the final target of the robot. Some Fuzzy and their combination methods/algorithms used by the researchers of localization using fuzzy algorithm in recent years is presented in Table I.

TABLE I. RECENT ODOR LOCALIZATION RESEARCH USING FUZZY

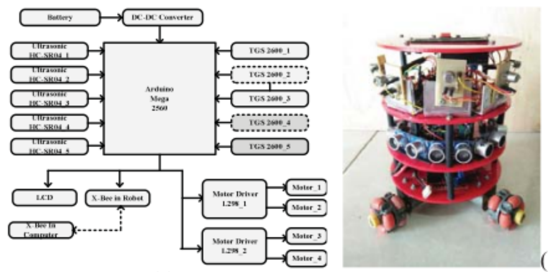
Year	Methods/Algorithm	References
2014	Fuzzy	[39]
2015	Fuzzy Fuzzy control based	[40] [2][7]
2016	Fuzzy-PSO	[41]
2017	Fuzzy-Kohonen	[42]

The research in [41] was only a simulation one, while the rest was done in real experimental environment. The fuzzy in [2], [7], [39] , and [40] were successful in localizing the odor. The fuzzy logic in [42] was combined with PSO in order to control the swarm robot to the target. It was successful in localizing the odor source in short time. However, none of them used gas sensos as the inputs of fuzzy logic. Moreover, none of them analyzed the optimal distance of the gas sensors arrangement.

III. EXPERIMENTAL SET-UP

A. Block Diagram

In this study, a robot with two modes were built. It was equipped with a 5 TGS 2600 gas sensors that could be switched into 3 and 5 gas sensors modes. When the mode 3 was selected and the 3 fuzzy algorithm was used, then the 3 sensors will be activated. It also happened to the mode 5, for activiting 5 gas sensors, the step was only switch the toggle to the mode 5.



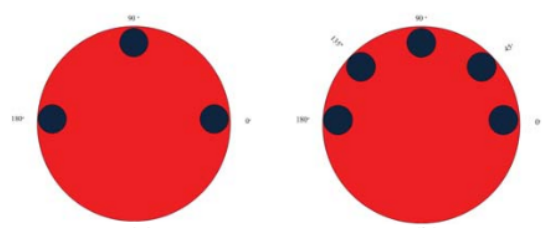
(a) (b)

Fig. 1. (a) Block Digram of the OSR, (b) OSR

The robot has diameter of 20 cm with round shape and it was also equipped with DC-DC converter that has function to convert 12V DC voltage into 5V DC voltage, 5 HC-SR04 utrasonic sensors as the distance sensors that can manage the distance of the robot to the obstacles and the wall, Arduino Mega 2560 as the controller of the robot, 4 DC motors with 2 L298D motor drivers as the mover of the robot, HMC5883L compas that has function to show the direction of the robot , and X bee module for robot communication. The diagram block of the robot is shown in Fig. 1.

B. Sensor arrangement

The arrangement of the gas sensors was shown in Fig. 2. For the 3 gas sensors mode, each of the sensor was placed in 0^0, 90^0, and 180^0, while for the 5 gas sensors was placed in 0^0, 45^0, 90^0, 135^0, and 180^0.



(a) (b)

Fig. 2. Sensor arrangement

C. Experimental Environment

The experiments in this study were conducted in a room with 3 m x 3 m arena. This arena was intended to limit the dispersion of the experimental gases. The experimental environments were set up using 4 scenarios, i.e.

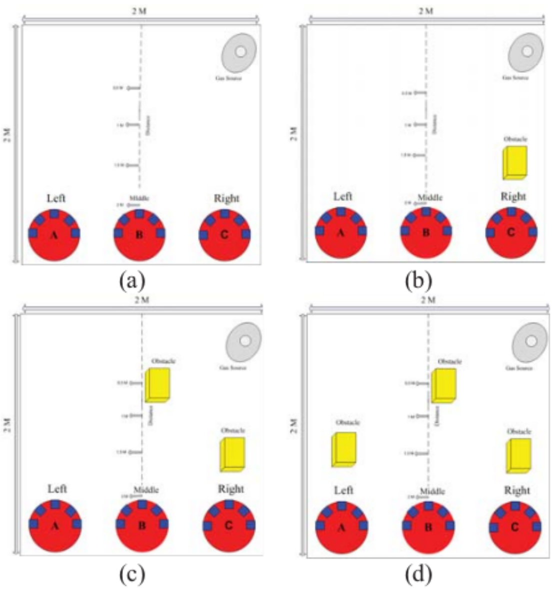


Fig. 3. Experimental Environment (a) No Obstacles, (b) 1 Obstacle, (c) 2 Obstacles, and (D) 3 Obstacles

D. *Fuzzy Logic*

The fuzzy logic in this study was implemented in 2 modes experiments, mode 3 and mode 5. Each of the fuzzy logic coding could be changed easily by pushing the switch button on the top of the OSR. The overall of the systems is almost the same. Each mode was consisted of the fuzzyfication, fuzzy rules, and the defuzzyfication process. However, the number of fuzzy rules of mode 5 was more than the mode 3. The fuzzy rules for mode 3 consisted of only 27 rules, while mode 5 needed 243 rules. The number of membership functions that was used can be calculated using the equation: y^x, where y is number of membership functions, and x is the number of input sensors. Thus, for 5 input sensors with 3 membership functions, the fuzzy rules was 243..

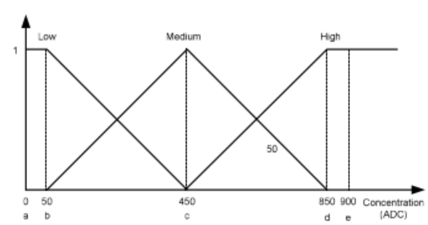


Fig. 4. Input membership function

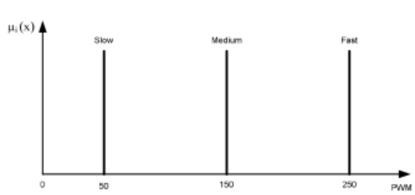


Fig. 5. Output membership function

In this research, 3 membership functions were used as the gas sensors input, i.e. Low, Medium, and High. The memberships functions of input and output can be seen in Fig. 3 and Fig. 4. The overall process of mode 3 fuzzy logic in this study can be seen in our previous project [43]. As stated above, the fuzzy logic process for mode 5 was the same with mode 3 fuzzy logic. The difference was only in the number of fuzzy rules. The Linguistic variable for gas sensors input and output can be seen in Table II. The membership functions of the output were in the singleton form, namely: Slow, Medium, and Fast. PWM 50 indicated Slow motion, while PWM 150 and 250 indicated Medium and Fast motion respectively. The defuzification in this research used Sugeno method. The implication function that was used in this research was Max-Min operation to certain membership function.

TABLE II. GAS SENSOR INPUT AND OUTPUT LINGUISTIC VARIABLE

INPUT		OUTPUT	
Gas Concentration (ADC)	Linguistic Variable	PWM Motor	Linguistic Variable
0-449	Low	50	Slow
50-849	Medium	150	Medium
450-900	High	250	High

IV. RESULT AND DISCUSSION

The experiment in this study was done in 4 scenarios, the trajectories of the robot were shown in Fig. 6 – Fig.9. The data of each experiment was shown in Table III – Table VI.

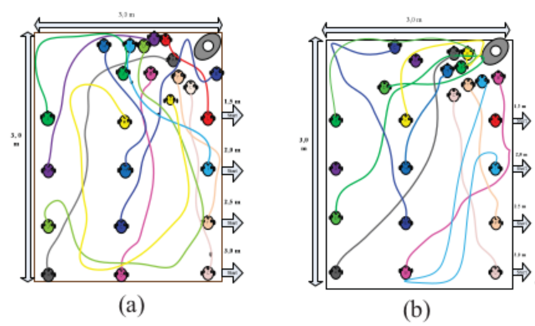


Fig. 6. OSR Trajectory in No Obstacle

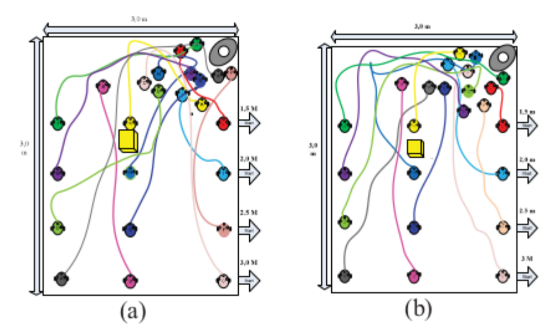
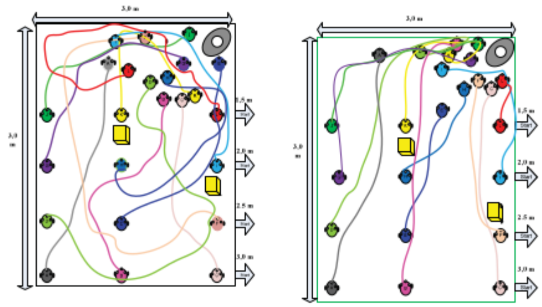
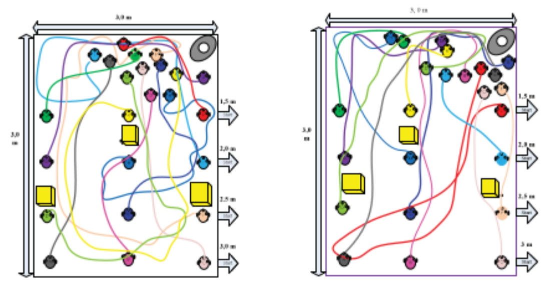


Fig. 7. OSR Trajectory in 1 Obstacle



(a) (b)

Fig. 8. OSR Trajectory in 2 Obstacle



(a) (b)

Fig. 9. OSR Trajectory in 3 Obstacle

TABLE III. OSR SEARCHING TIME IN NO OBSTACLES

Fuzzy Type	Starting Point	Time (s)			
		1.5	2.0	2.5	3.0
Mode 3	Right	32 (L)	35 (I)	42 (F)	48 (C)
	Middle	74 (K)	36 (H)	65 (E)	52 (B)
	Left	34 (J)	40 (G)	80 (D)	60 (A)
Mode 5	Right	25 (L)	85 (I)	38 (F)	41 (C)
	Middle	40 (K)	25 (H)	70 (E)	58 (B)
	Left	43 (J)	30 (G)	78 (D)	59 (A)

TABLE IV. OSR SEARCHING TIME IN 1 OBSTACLE

Fuzzy Type	Starting Point	Time (s)			
		1.5	2.0	2.5	3.0
Mode 3	Right	28 (L)	29 (I)	38 (F)	54 (C)
	Middle	32 (K)	36 (H)	42 (E)	47 (B)
	Left	34 (J)	38 (G)	45 (D)	63 (A)
Mode 5	Right	15 (L)	29 (I)	25 (F)	48 (C)
	Middle	21 (K)	47 (H)	31 (E)	39 (B)
	Left	33 (J)	43 (G)	52 (D)	48 (A)

TABLE V. OSR SEARCHING TIME IN 2 OBSTACLES

Fuzzy Type	Starting Point	Time (s)			
		1.5	2.0	2.5	3.0
Mode 3	Right	50 (L)	50 (I)	52 (F)	48 (C)
	Middle	40 (K)	50 (H)	57 (E)	56 (B)
	Left	38 (J)	50 (G)	76 (D)	52 (A)
Mode 5	Right	28 (L)	37 (I)	36 (F)	37 (C)
	Middle	39 (K)	29 (H)	30 (E)	48 (B)
	Left	38 (J)	43 (G)	45 (D)	59 (A)

TABLE VI. OSR SEARCHING TIME IN 3 OBSTACLES

Fuzzy Type	Starting Point	Time (s)			
		1.5	2.0	2.5	3.0
Mode 3	Right	32 (L)	35 (I)	42 (F)	48 (C)
	Middle	74 (K)	36 (H)	65 (E)	52 (B)
	Left	34 (J)	40 (G)	80 (D)	60 (A)
Mode 5	Right	70 (L)	25 (I)	24 (F)	36 (C)
	Middle	22 (K)	33 (H)	39 (E)	57 (B)
	Left	28 (J)	37 (G)	42 (D)	58 (A)

In each scenarios, the robot was placed in the 12 starting points, In Fig. 6 – Fig. 9, the starting points of experiments were represented in the arrows (in the right side of each figures) that showed 1.5 m, 2.0 m, 2.5 m, and 3.0 m away from the source. Each distances had 3 sub positions of starting point, i.e, Left, Middle, and, Right. They were named A, B, C for the 3 m distance; D, E, and F for 2.5 m distance; G, H, and I for 2.0 m distance; and J, K, and L for 1.5 m distance. The position labels (A-L) were shown in the middle of each circles in Fig. 6 – Fig. 9.

In Fig. 6 – Fig.9, Some of OSR trajectories showed a deviation. For example in Fig. 6 (a) position D, Fig. 6 (b) position I, Fig. 8 (a) position F, Fig. 9 (a) position F and I, and Fig. 9 (b) position L, the OSR navigated to the backside of the source and followed the experimental wall, however it could finish their task in about 60 - 86 s (Table V and Table VI). The condition might occur due to the OSR have not detected the occurrence of the source in that place and tried to itinerate by following the wall. However, when they had found the odor, they activated their fuzzy logic and navigated to the source by relying on the concentration of the odor that they sensed.

In Fig. 6 (a) in K position (Table III), the OSR needed more time in reaching the source (74 s), the OSR moved backward and continued to go forward until the position B, then made U turned and moved back to search the odor source. It happened due to at first minute, it sensed the odor concentration at its backside, however, when it moved back, it lost the odor, therefore, it continued to go forward about 22 s. This OSR was programmed to move back when it did not sense the odor for 20 s, therefore, it made u turned and continued to go forward to the source, when it sensed the odor, it activated the fuzzy logic, and finally found the odor source. In Fig. 6 (b), in I position (Table III), the same problem in position K of Fig 6 (a) happened, the OSR did not went forward, except turned backward, however, it could finally finished the searching task in 85 s.

In Fig. 7 (a) and 7 (b), the OSR seemed to be successful in navigating to the odor source in every position of starting points without any difficulties. The OSR in this environment (in 1 obstacle) could reach the target more quickly than the no obstacles environment (See Fig. 7 and Table IV). The OSR moved forward since it started its searching task. Although, there is an obstacle set up in this environment, the OSR could find the location of the source. It is due to, the OSR have sensed the occurrence of the odor at the first time it started the searching task, and therefore, it did not move its direction. It just navigated forward using the concentration data. Although both of the mode 3 and mode 5 have been successful in finding the odor, however, mode 5 represented faster and simpler path than mode 3.

In Fig. 8 (a) there were deviation in position D and position L. In position D, the OSR did not moved forward but moved to its right side, it changed its direction when it sensed the odor and continued move forward until it reach the odor. In position L, the OSR have found the location of the source in its first 20 s searching (See Fig. 8 and Table V), however it did not stop, it seemed that the concentration it sensed was not reach the source setting concentration, therefore, it just kept to move. In Fig 8 (b), the OSR could reach the source with only a few errors. Most of the position of OSR starting point gave the best result. In this experiment (Fig. 8 (b)), the OSR also gave the faster and simpler navigation.

In Fig. 9 (a) a deviation occurred in position F, H, and K (See also Table VI). In position F, the OSR moved to the left side first before it continued to navigate to the odor source, however, it was still able to reach the source. The big error occurred in K position, although its starting point was really closed to the target, it itinerated to the opposite side of the source. It seemed that it got misinformation about the odor concentration that it should follow. Therefore, it wasted a long time travelling not to the source. In H position, although the OSR had time to turned back its position, however, its error was not so fatal. In Fig 9 (b), only the position L gave an error, although its starting point was so closed to the source, however, it needed 70 s to reach it. It seemed that it could not detect the odor; therefore, its trajectory was out of the determined path.

V. CONCLUSION

From the experiments, it can be concluded that there was no significant difference between using 3 gas sensors or 5 gas sensors. Both of them gave advantage. If it needs low cost and low computation, an OSR equipped with 3 gas sensors could be used. However, if it needs a faster and simpler navigation, a 5 gas OSR could be used. Although in 5 gas OSR, there were a lot of fuzzy rules than 3 gas OSR, however, the computation was not so high, the micro controller that was used, was still able to manage it. It was proved by the faster time that the OSR needed in finding the source.

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