Gas Source Localization using Grey Wolf Optimizer

S.M.Mamduh[1, 2], K.Kamarudin[1,3], A.Y.M.Shakaff[1,3], A.Zakaria[1,3], R.Visvanathan[1,3], A.S.A.Yeon[1,3], L.M.Kamarudin[1,4] and A.S.A.Nasir[5]

[1]*Centre of Excellence for Advanced Sensor Technology (CEASTech), Universiti Malaysia Perlis (UniMAP), Arau, Perlis 02600.*

[2]*Pusat Pengajian Kejuruteraan Mikroelektronik, Universiti Malaysia Perlis (UniMAP), Arau, Perlis 02600.*

[3]*Pusat Pengajian Kejuruteraan Mekatronik, Universiti Malaysia Perlis (UniMAP), Arau, Perlis 02600.*

[4]*Pusat Pengajian Kejuruteraan Komputer dan Perhubungan, Universiti Malaysia Perlis (UniMAP), Arau, Perlis 02600.*

[5]*Fakulti Teknologi Kejuruteraan, Universiti Malaysia Perlis (UniMAP), Padang Besar, Perlis 02100.*

smmamduh@unimap.edu.my

***Abstract*—Gas source localization is an ability which has yet to be successfully implemented in synthetic systems although it is widely exhibited by various organisms. Although single robot implementation has been explored, it is still prone to single point failures and is limited in sporadic gas dispersion conditions. Swarm intelligence based algorithms such as Particle Swarm Optimization and Ant Colony Optimization has shown the feasibility and advantage of using multi-robot strategy for gas source localization. This paper explores Grey Wolf Optimizer (GWO) as an alternative algorithm for gas source localization. It was found that, although some GWO search behavior is favorable for gas source localization, the algorithm may fail when used with low numbers of robots. The algorithm was able to localize the peak gas concentration in approximately 30 minutes. The best success rate is found to be 72% with 7 searcher robots.**

***Index Terms*—Gas Source Localization; Grey Wolf Optimizer; Mobile Olfaction; Swarm Intelligence.**

I. Introduction

Animals with relatively low levels of intelligence such as dogs, silkworm moth, lobsters and blue crab have all exhibited gas source localization capabilities for hunting, foraging and mating [1]. Remarkably, these simple beings are able to complete their task in an unknown environment in which unpredictable airflow affects the gas dispersion.

The ability to track and find gas sources has enabled these animals to maintain the continuity of their species. This feat; although appear to be simple, is yet to be fully imitated by synthetic systems produced by humans. Being able to replicate this skill in robots may offer a deeper understanding of animal behavior and opens up the possibility to use the knowledge gained in many applications. Motivated by the myriad of potential applications based on gas sensing, gas mapping [2] and localization capability, a considerable amount of interest has been generated in this research field.

Although various single agent algorithms have been presented, few works on swarm intelligence for gas source localization have been presented [3, 4]. In this paper, Grey Wolf Optimizer (GWO) algorithm is proposed for gas source localization. It is envisaged that the search behavior of Grey Wolves encircling the prey would be favorable for gas source localization.

II. Literature Review

Marjovi and Marques [5, 6] proposed a formation based swarm tracking algorithm derived from the findings of previous works [7]. Based on a probabilistic model of sensor coverage of the plume in laminar flow, an optimized formation for plume tracking was proposed to maximize the probability of finding an odor plume. The optimum formation was found to be an equally spaced diagonal robot formation in relative to the wind direction. The distance of the robot from each other is a function of wind speed and affected by environmental conditions such as obstacles. The method was tested and validated in simulations and experiments in a controlled environment.

The Particle Swarm Optimization algorithm is an evolutionary technique inspired by the dynamics of social organisms while foraging [8]. This algorithm was one of the earliest swarm intelligence algorithm implemented for gas source localization [9, 10]. In this study, PSO was compared with biased random walk and gradient following algorithms. The algorithm was simulated in a turbulent dominated gas dispersion environment using 10 robots to locate 5 gas sources. Results suggest that PSO algorithm performs better and more stable in unstable wind conditions. However, in practical conditions, the robots may not be able to synchronize in each iteration and function asynchronously, prompting a modified algorithm to be proposed [11]. The asynchronous algorithm uses the latest information from surrounding robots and does not wait for the particular iteration to end. Even when operating asynchronously, the algorithm was reported to successfully locate the source of the gas in simulated gas dispersion conditions.

Ferri et al. proposed Explorative PSO (EPSO) algorithm to increase the exploration of the immediate surrounding area of the robot and reducing the possibility for the swarm of being trapped in a local maxima [12]. In simple terms, the robot adjusts its position to avoid being too close with a previously sampled point; at the distance which is determined by the measured concentration peak and the frequency of the concentration peak. Simulations have suggested that the EPSO algorithm is more efficient than the normal PSO algorithm.

Dorigo, Maniezzo and Colomi proposed an optimizing algorithm inspired by the social foraging behaviour of ants [13]. This algorithm was abstracted and then applied a modified variant to gas source localization task in the diffusion-dominated environment [14]. There are two types of robots, searchers and residents. The searcher searches for higher concentrations of gas in the search space. The search task was broken into three stages; local traversal search, global search and pheromone update. The pheromone is a function of the measured concentration gain when moving towards another robot. Once a candidate source location is found by the searcher, it becomes a resident and does not search for other possible solutions. The robot with the lowest measured concentration will revert back to the searcher behavior. The location where the ants converge is the source location. The algorithm was able to locate two gas sources in the tested search space. However, more realistic conditions are required to verify the algorithm's reliability in variable airflow conditions.

GWO is a recently developed optimizing algorithm which is divided into three stages; tracking the prey, encircling the prey, and attacking the prey [15]. The search behavior is envisaged to be favourable for gas source localization as the robot swarm will try to surround the gas source before closing in on the source. The gas dispersion where airflow is present, produces an elongated plume from the source downwind with unpredictable peaks in the plume [5]. Hence, the swarm will not overshoot the gas source as reported by other algorithms [12, 13]. The GWO search mechanism will be discussed in the Methodology section.

III. METHODOLOGY

The GWO algorithm is inspired by grey wolves (*Canis lupus*); mimicking its leadership hierarchy and hunting mechanism [15]. This recently proposed algorithm has been implemented in a number of applications such as unit commitment problem [16], assembly flow shop scheduling problem [17] and training multi-layer perceptron [18]. In this research, GWO is implemented for gas source localization task.

Robots are divided based on social hierarchy, where the best solution is named as the alpha (α), the second best beta (β) and third best delta (δ) based on continuously sampled data. The other robots are assumed to be omega (ω). The ω robots generally are guided by the α, β and δ robots. The robots will encircle the prey (source); described as:

$$\vec{D}(t) = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}(t) \tag{2}$$

where: $\vec{D}$ = Encirclement vector of the robot
$\vec{X}_p$ = Predicted position of the gas source
$\vec{X}$ = Movement vector of the robot

$\vec{A}$ and $\vec{C}$ are coefficient vectors which are calculated as:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1(t) - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{4}$$

where: $\vec{a}$ = Components that are linearly decreased from 2 to 0 during each iterations
$\vec{r}_1$ and $\vec{r}_2$ = Random variables in [0,1]

The result of these equations is the robots will encircle the point where the source is predicted to be. The reduction of $\vec{a}$ will cause the robots behaviour to slowly transition from exploring ($\vec{A} \geq 1$) to exploitation ($\vec{A} < 0$).

Based on Equations (5) to (7), the hunting behaviour of the wolves may be described. It is assumed that the three fittest wolves guide the rest of the wolves in the hunt; in this research, the α, β and δ robots. The fitness of the robots is determined by the measured gas concentration of each robot; higher concentration values mean higher fitness. The waypoint updates for these three robots may be described as:

$$\begin{aligned} \vec{D}_\propto &= \left|\vec{C}_1 \cdot \vec{X}_\propto - \vec{X}\right| \\ \vec{D}_\beta &= \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta &= \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \end{aligned} \tag{5}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \tag{6}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{7}$$

In conclusion, the set of equations presented allows the robots to explore the search space guided by the α, β and δ robots. Based on the positions of these three robots, a possible solution is proposed and the robots encircle the possible solutions. As the robots perform each iteration, the linear reduction of $\vec{a}$ and thus, $\vec{A}$, the robots will gradually converge on the source. In this research, the coefficient $\vec{a}$ is reduced by 0.1 after each iteration, allowing a maximum of 20 iteration steps before $|\vec{a}\,| = 0$. Figure 1 depicts the pseudocode for the GWO algorithm.

```
GWO Algorithm
Initialize parameters
Set first waypoint away from the source
move(first waypoint)
while (!Max number of iterations)
        move (next waypoint)
        if (arrived at waypoint)
                Sample sensor readings
                Broadcast data
        end
        while (!All agents arrive at waypoint)
                wait
                Listen for data from other      robots
        end
        Update a, A, and C
        Update fitness
        Update  α, β and δ
        Update waypoint
end
```

Figure 1: GWO pseudocode for gas source localization

The algorithm is implemented and then simulated in *Webots* robot simulation software using the data stream collected in previous research [19]. The 3m × 6m testbed, communication backbone and gas sensor model was fully emulated in the *Webots* simulation. Furthermore, using a 2-hour data stream collected in the testbed, the real gas dispersion can be recreated in the simulation environment, ensuring repeatable and accurate simulation results.

IV. RESULTS

The algorithm was implemented using 3, 5, 7, 10 and 15 robots. Each case was run 25 times and the performance of each case is compared. This section will discuss the search behavior first before exploring the effect of different agent numbers to the search performance.

A. *Search Behaviour*

The robot movement during gas source localization task using GWO (Run 1) is shown in Figure 2. Due to the nature of the algorithm where each agent updates its next position based on other alpha, beta and delta robots' positions, the robots tend to move close to each other. Movement in close vicinity to each other while trying to encircle the solution causes robots to impede each other's movements as they move to the next position. However, there is reduced avoidance when the robots are in exploring stage than when in constriction stage (close to source).

Robots using GWO are able to converge on the peak concentration point. As reported in previous works on GWO, the robots are able to locate the peak concentration, due to the concentration based fitness function. This behavior is also exhibited by previous works on gas source localization using various versions of PSO and ACO. This highlights one of the difficulties in gas source localization – peak concentration does not necessarily occur at the source.

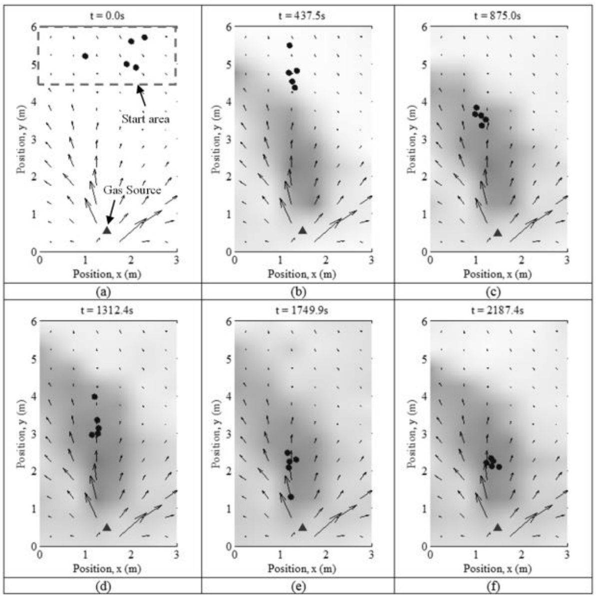

Figure 2: GWO gas source localization

B. *Performance of Different Number of Robots*

Figures 3-6 depict the effect of different agent number on swarm robots using GWO algorithm. Similar to other swarm intelligence algorithms, the number of iteration decreases as a number of agent increases as shown in Figure 3. The average error from source also decreases slightly as agent number increases as shown in Figure 4. However, in Figure 5, the time to complete the gas source localization task increases with agent number. The increase in time is due to competition for space and collision avoidance manoeuvre while traversing the search space. The avoidance manoeuvre is further exacerbated due to the encircling behaviour exhibited by GWO which usually causes robots path to cross each other.

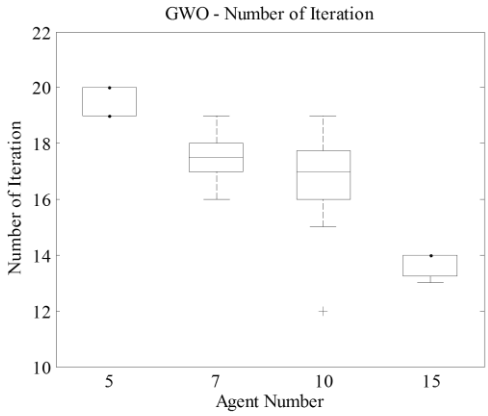

Figure 3: Number of iteration with different number of robots

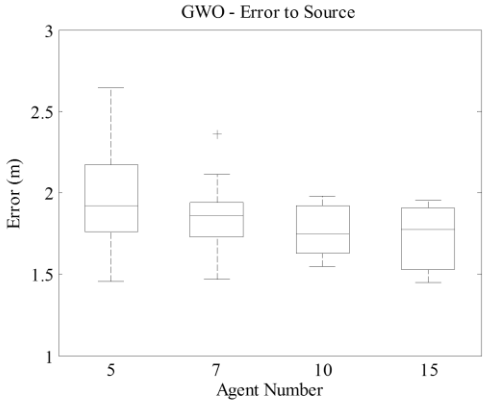

Figure 4: Error to a source with a different number of robots

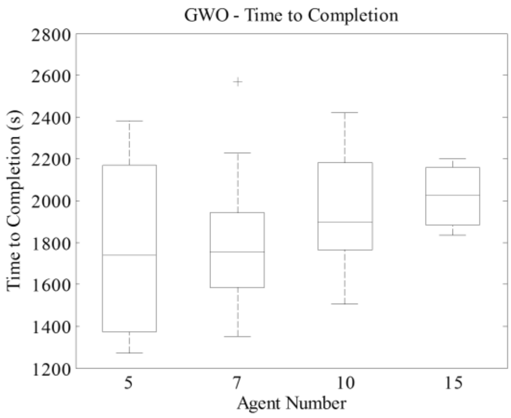

Figure 5: Time to completion with a different number of robots

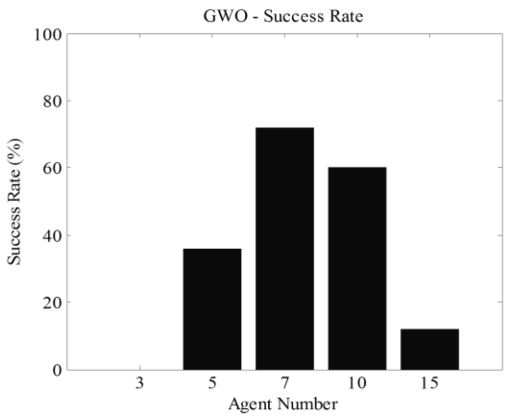

Figure 6: GWO performance with different number of robots

Interestingly, in Figure 6, the algorithm fails completely if conducted with three agents; which is why the discussion up to this point does not include statistics for three agent systems. As the robot using GWO updates their next position based on the position of the three fittest agents, deploying only three robots causes there to be lack of solutions to be considered. As a result, the robots update their position based on the same three robots including themselves, causing one of the $\vec{D}$ in Equation (6) to be 0. This in turn destroys robot hierarchy and the prey circling concept which is being mimicked in the algorithm. The success rate improves when there are five and seven agents as the hierarchy is restored; as reported in previous works. However, increasing the agent number beyond seven agents caused reduction in success rate due to increased frequency of irrecoverable collisions between robots due to competition for space.

V. CONCLUSION

GWO algorithm was successfully implemented for gas source localization. It was observed that the strategy of robots encircling the 'prey' although may be useful for gas source localization, it causes the robot to tend to maneuver close to each other. This causes the performance of the algorithm to drop as robots need to avoid each other. It was also observed that the performance of the algorithm increases as the number of robots increases to 7 with 72% success rate. If the number of agents are increased beyond 7 robots, the success rate and time to completion decrease.

ACKNOWLEDGMENT

Work by the authors was partially supported by the Universiti Malaysia Perlis Short Term Grant (STG 9001-00561) entitled "Improved Gas Source Localization Through Path Planning".

REFERENCES

[1] Fraenkel, G.S. and D.L. Gunn, *The orientation of animals, kineses, taxes and compass reactions*. 1961: Dover Publications.

[2] Kamarudin, K., et al., "Flexible and Autonomous Integrated System for Characterizing Metal Oxide Gas Sensor Response in Dynamic Environment," *Instrumentation Science & Technology*, vol. 43(1), 2015.: pp. 74-88.

[3] Mamduh, S., et al., Comparison of Braitenberg Vehicles with Bio-Inspired Algorithms for Odor Tracking in Laminar Flow. *Australian Journal of Basic & Applied Sciences*, vol 8(4). 2014.

[4] Mamduh, S.M., et al., "Braitenberg swarm vehicles for odour plume tracking in laminar airflow," *IEEE Symposium on Computers & Informatics (ISCI)*, 2013.

[5] Marjovi, A. and L. Marques, "Swarm robotic plume tracking for intermittent and time-variant odor dispersion," *2013 European Conference on Mobile Robots (ECMR*), 2013.

[6] Marjovi, A. and L. Marques, "Multi-robot odor distribution mapping in realistic time-variant conditions," *2014 IEEE International Conference on in Robotics and Automation (ICRA)*, 2014.

[7] Marjovi, A. and L. Marques, "Optimal spatial formation of swarm robotic gas sensors in odor plume finding," *Autonomous Robots*, vol 35(2-3), 2013, pp. 93-109.

[8] Kennedy, J. and R. Eberhart. "Particle swarm optimization," *IEEE International Conference on Neural Networks*, 1995.

[9] Marques, L. and A.T. de Almeida, "Finding Odours Across Large Search Spaces: A Particle Swarm-Based Approach," in *Climbing and Walking Robots*, Springer Berlin Heidelberg, 2005, p. 419-426.

[10] Marques, L., U. Nunes, and A.T. de Almeida, "Particle swarm-based olfactory guided search," *Autonomous Robots*, vol. 20(3), 2006. pp. 277-287.

[11] Akat, S.B., V. Gazi, and L. Marques, "Asynchronous particle swarm optimization-based search with a multi-robot system: simulation and implementation on a real robotic system," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 18(5), 2010. pp. 749-764.

[12] Ferri, G., et al., "Explorative Particle Swarm Optimization method for gas/odor source localization in an indoor environment with no strong airflow," *IEEE International Conference on Robotics and Biomimetics*, 2007.

[13] Dorigo, M., V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 26(1), 1996, pp. 29-41.

[14] Yuhua, Z., L. Dehan, and C. Weihai. "Swarm robotic odor source localization using ant colony algorithm," *IEEE International Conference on Control and Automation*, 2009.

[15] Mirjalili, S., S.M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, 2014. pp. 46-61.

[16] Kamboj, V.K., "A novel hybrid PSO–GWO approach for unit commitment problem," *Neural Computing and Applications*, 2015, pp. 1-13.

[17] Komaki, G.M. and V. Kayvanfar, "Grey Wolf Optimizer algorithm for the two-stage assembly flow shop scheduling problem with release time," *Journal of Computational Science*, vol. 9, 2015, pp. 109-120.

[18] Mirjalili, S., "How effective is the Grey Wolf optimizer in training multi-layer perceptrons," *Applied Intelligence*, vol. 43(1), 2015, pp. 150-161.

[19] Syed Zakaria, S., et al., "Development of a Scalable Testbed for Mobile Olfaction Verification," *Sensors*, vol. 15(12), 2015, pp. 29834.