Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 6-15

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

Comparison of Braitenberg Vehicles with Bio-Inspired Algorithms for Odor Tracking in Laminar Flow

S.M. Mamduh, K. Kamarudin, A.Y.M. Shakaff, A. Zakaria, A.H. Abdullah

Centre of Excellence for Advanced Sensor Tehcnology (CEASTech),Universtiti Malaysia Perlis, Lot 21, Taman Muhibbah, Jalan Jejawi-Permatang, Arau, 02600, Perlis, MALAYSIA

ARTICLE INFO

Article history:
Received 20 November 2013
Received in revised form 24 January 2014
Accepted 29 January 2014
Available online 25 February 2014

Keywords:
mobile olfaction; swarm robots; Braitenberg vehicles; odor plume tracking

ABSTRACT

Odor gas tracking is a capability exhibited by animals but sorely needed by humans for applications in areas such as security, search and rescue and industrial monitoring; amongst others. The research documented in this document proposes a new algorithm based on Braitenberg vehicle that mimics the strategy of animals and insects for odor tracking. Simulation results show that the proposed algorithm was able to independently track an odor plume to its source, comparable to other prominent algorithms. Deployment of a multirobot system using the same algorithm shows an improvement in the completion of the plume tracking task in terms of completion time. Furthermore, comparisons with other algorithm have shown that the proposed algorithm performs better than the typical single and multi-robot strategies.

To Cite This Article: S.M. Mamduh, K. Kamarudin, A.Y.M. Shakaff, A. Zakaria, A.H. Abdullah, Comparison of Braitenberg Vehicles with Bio-Inspired Algorithms for Odor Tracking in Laminar Flow. ***Aust. J. Basic & Appl. Sci.,*** *8(4): 6-15, 2014*

INTRODUCTION

Animals with seemingly low intelligence have exhibited the ability to track odor for hunting, foraging and mating (Fraenkel and Gunn 1961). In an unknown environment, the task is harder to complete as the odor dispersal is affected heavily by the unpredictable airflow. However, these simple beings have the capability to address the problem with minimal effort and maintain continuity of their species. Such examples of odor source localization by natural systems have been going on for thousands of years. Amazingly, these simplistic solutions have prevailed even in a highly unpredictable and dynamic environment. As there are many potential applications for odor source localization, mimicking these strategies has been the subject of interest of researchers.

Currently, interest in odor localization is increasing due to the growing need for environmental monitoring, security, surveillance, industrial monitoring, agricultural, humanitarian demining and search and rescue (A. Lilienthal, Loutfi, & Duckett, 2006). The common practice is by using handheld devices or trained dogs for gas source localization. Unfortunately, these methods require trained personnel which are prone to error, fatigue and needs supervision. Successful implementation of source localization on mobile robots can be desirable to increase success and reliability in the said applications. Dependency on trained dogs for drug tracking, for example, can be eliminated. Furthermore, advancements in swarm robotics allow for simpler strategies for solving complex problems.

II. Related Work:

Inspired by biological systems which has successfully addressed this problem (Byers, 1996; Dusenbery, 1989; J. S. Kennedy & Marsh, 1974; Rieser, Yonas, & Wikner, 1976; Willis, 2008); much effort has been directed to replicate and enhance the behaviors of these beings in the laboratory. Previous researches has focused on single robot and multi-robot application, while looking at ways of modeling an odor plume with the smallest amount of data, to provide useful information for robot navigation. As biological systems tend to be reactive, most research has been focusing on this type of system (Kowadlo & Russell, 2008).

However, the current technology is heavily outperformed by the natural counterparts (Hernandez Bennetts, Lilienthal, Neumann, & Trincavelli, 2012). For example, chemoreceptors on animals detect chemicals faster and are tuned to the type and concentration and odor of interest. Furthermore, wildlife at times exhibits a level of intelligence in decision making that sometimes can only be described as experience and instinct (Ishida, Nakamoto, Moriizumi, Kikas, & Janata, 2001; A. Lilienthal, Reimann, & Zell, 2003). Hence, several

Corresponding Author: S.M. Mamduh, Centre of Excellence for Advanced Sensor Tehcnology (CEASTech),Universtiti Malaysia Perlis, Lot 21, Taman Muhibbah, Jalan Jejaw-Permatang, Arau, 02600, Perlis, MALAYSIA.
E-mail: smmamduh@ieee.org

modifications have been made to bio-inspired systems so that it emulates strategies exhibited by natural systems rather than directly mimicking it.

A. Single Robot Algorithm:

In general, single robot odor localization algorithm can be classed into four groups, namely, chemotaxis, anemotaxis, vision driven and infotaxis. Chemotaxis is a gradient driven motion; in this case, based on the concentration of the target odor (Atema, 1996). Wind guided search is classed as anemotaxis (J. S. Kennedy & Marsh, 1974). This class of search strategy is based on the assumption that odor sources must lie upwind from a detected odor. As such, entities that use this strategy tend to move upwind to find an odor source. Vision driven search strategies use vision based devices in order to locate odor sources (Ishida, Tanaka, Taniguchi, & Moriizumi, 2004). Gas mapping is in general the most complex, as it generally uses collected data to estimate the likely position of the source (Ramirez, Lopez, Rodriguez, de Albornoz, & De Pieri, 2011).

Chemotaxis strategies include *E. Coli* algorithm, Biased Random Walk (BRW) and some Braitenberg based algorithm are strictly chemotactic. Algorithms mimicking them and its enhancements have been proposed by previous researches (Harvey, Tien-Fu, & Keller, 2008a; Ishida *et al*., 1995; A. J. Lilienthal & Duckett, 2003; Loutfi & Coradeschi, 2002; Marques, Nunes, & de Almeida, 2002; R. Andrew Russell, Bab-Hadiashar, Shepherd, & Wallace, 2003; R. A. Russell, Thiel, Deveza, & Mackay-Sim, 1995; Sandini, Lucarini, & Varoli, 1993). This type of algorithm can be identified easily as during plume traversal, its motion tends upwards a positive gradient of chemical concentration. The robot's behavior is not directly affected by airflow or by any other parameters.

Anemotaxis based strategies such as silkworm moth algorithm, dung beetle algorithm (zigzag), casting, surge-cast, spiral-surge and their enhancements have been proposed and discussed. These algorithms usually incorporate some chemical sensing to detect odor plumes; but their plume traversal movement is determined by the direction of the wind. The input from gas sensors are not used directly to guide the robot to the source. The general tendency for this set of algorithm is to move upwind from where odor is detected. Simulation runs and real robot implementations have been presented by many researchers (Harvey, Tien-Fu, & Keller, 2008b; A. T. Hayes, Martinoli, & Goodman, 2001; Adam T. Hayes, Martinoli, & Goodman, 2003; Ishida, *et al*., 1995; Ishida, Kagawa, Nakamoto, & Moriizumi, 1996; Ishida, Suetsugu, Nakamoto, & Moriizumi, 1994; Thomas Lochmatter & Alcherio Martinoli, 2009; Marques, *et al*., 2002; Nurzaman, Matsumoto, Nakamura, Koizumi, & Ishiguro, 2009; R. Andrew Russell, *et al*., 2003; R. A. Russell, *et al*., 1995).

New research has proposed vision to further aid odor localization(Ishida, *et al*., 2004; Ishida, Ushiku, Toyama, Taniguchi, & Moriizumi, 2005; Jianhua, Xiaojun, Lingyu, & Minglu, 2010; Ping, Qing-Hao, & Ming, 2010; Wang, Meng, & Zeng, 2012). The researches publish methods that use visual cues for determining the possible odor source and verify it using chemical sensors.

Mapping based methods uses probability and information theory to estimate gas sources by building concentration maps based on different models (Farah & Duckett, 2002; Ishida, *et al*., 2001; Kazadi, Goodman, Tsikata, Green, & Lin, 2000; Ramirez, *et al*., 2011). This type of algorithm usually requires relatively high amounts of processing power or memory on the target robot platform.

B. Multi Robot Algorithm:

In order to further optimize the solution, swarm robotics has been introduced. Although implementing swarm robots on a problem adds hardware complexities such as communication dependencies and task management (Cao, Fukunaga, Kahng, & Meng, 1995) it is capable of solving complex problems using simpler algorithms (Dudek, Jenkin, Milios, & Wilkes, 1993). The basic concept of swarm robots is generally a multi-robot system that interacts with each other in order to achieve a set of objectives(Dudek, Jenkin, Milios, & Wilkes, 1996). By using multi-robot systems, the search space for each robot can be reduced, more data can be collected faster, more accurate decisions can be made and objectives may be fulfilled by collective behavior.

For odor localization, algorithms that have been implemented to date are either based on single robot algorithms or swarm intelligence theories. Spiral-surge (Hayes, Martinoli, & Goodman, 2001, 2002; Marjovi, Nunes, Sousa, Faria, & Marques, 2010) and infotaxis has been implemented on a real robot swarm successfully to locate an odor source. Examples of swarm intelligence that have been implemented are Ant Colony Algorithm (Yuhua, Dehan, & Weihai, 2009)and Particle Swarm Optimization (Ferri *et al*., 2007; Marques, Nunes, & Almeida, 2006).

More comprehensive reviews of methods have been presented in previous reviews (Ishida, Wada, & Matsukura, 2012; Kowadlo & Russell, 2008). They have different ways of presenting the previous researches done in this field, however, it does not contradict with this interpretation. The differences between all the reviews are due to diverse views on recent researches and the different ways each author presents their findings.

III. Problem Statement:

Current methods of odor plume tracing can be inefficient as they do not move directly towards the source of the odor. Bio-inspired algorithms for single robots, for example generally require robots to move in a direction which is thought to be the direction of a gas source and correct its movement when it finally leaves the plume. In contrast, previous works on the Braitenberg algorithm shows that it has the capability to navigate directly towards the source of the plume by constantly correcting the robot path(Mamduh *et al*., 2013).

Currently, swarm intelligence algorithms that have been implemented have limitations if any member of the robot is separated from the swarm. For example, in PSO based algorithms, an individual element cannot function without the other elements to compare its fitness score. Therefore, the single element may reduce to a single robot doing a local search or a BRW, depending on its implementation. By using an algorithm that can be used in either single or multi-robot configuration can solve this issue; hence the Braitenberg algorithm.

IV. Bio-Inspired Odor Tracking Algorithms:

A. Casting:

The same casting algorithm as Li *et al*. and Lochmatter *et al*. presented was implemented (Li, Farrell &Card, 2001; Lochmatter, Raemy, Matthey, Indra, & Martinoli, 2008).A robot in the plume moves upwind at an angle until it detects that it is out of the plume after a certain distance or time. The robot then turns and moves perpendicular to the wind until it reacquires the plume. Once in the plume, the robot moves upwind at an angle again. The pseudo-code of its implementation is presented in List. 1.

List. 1: Pseudo-code for Casting Algorithm

```
reset();
while(!found_souce)

if (inside_plume)
state_upwind_surge();

elseif(!inside_plume)
find_cast_direction();
state_crosswind_find();
endif;

endwhile;
```

B. Surge-Spiral:

The implemented surge-spiral algorithm is similar to the one proposed by Hayes *et al*. and Lochmatter *et al*.(A. T. Hayes, Martinoli, & Goodman, 2002; T. Lochmatter & A. Martinoli, 2009). However the algorithm was modified so that it has a single spiral gap parameter. Unlike casting, the robot moves straight upwind in the plume until it loses the plume after a certain distance or time. Once it loses the plume, the robot tries to reacquire the plume by moving in a spiral motion with a gap size. The robot will resume upwind surge when it finds the plume again. The pseudo-code for the implementation of the surge-spiral algorithm is displayed in List. 2.

List. 2: Pseudo-code for Surge-Spiral Algorithm

```
reset();
while(!found_souce)

if (inside_plume)
state_upwind_surge();

elseif(!inside_plume)
state_spiral_find();
endif;

endwhile;
```

C. Surge-Cast:

The surge-cast algorithm is a modification from the surge-spiral algorithm as proposed by Lochmatter *et al*.(T. Lochmatter & A. Martinoli, 2009). Instead of spiraling to find the lost plume, the robot commits to a crosswind movement. Similar to surge-spiral algorithm, the robot moves upwind until it loses the odor plume. However, once it loses the plume, it moves perpendicular to the wind for a set distance. If it does not find the plume, turns back and moves perpendicular to the wind again. To decide which way to cast, wind direction measurements is taken to estimate which side the robot left the plume. The implementation of the algorithm is shown in List. 3.

List. 3: Pseudo-code for Surge-Spiral Algorithm

```
reset();
while(!found_souce)

if (inside_plume)
state_upwind_surge();

elseif(!inside_plume)
find_cast_direction();
state_crosswind_find();
endif;

endwhile;
```

D. Particle Swarm Optomization:

PSO algorithm is a technique originally proposed by Kennedy and Eberhart (J. Kennedy & Eberhart, 1995). It is derived from the behavior of flocking animals while searching for food such as birds and fishes. In this research, the algorithm that was implemented is similar to the one implemented by Marques *et al*. (Marques, Nunes, & Almeida, 2006) and modified as simulated by Ferri *et al*.(Ferri *et al*., 2007).

In the original formulation, it is assumed that there exists of a group of searching elements (called particles) that traverses across a D-dimensional space based on these equations:

$$v_i(t) = \varphi v_i(t-1) + \rho_1(x_{pbesti} - x_i(t)) + \rho_2(x_{gbest} - x_i(t)) \quad (1)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (2)$$

where v_i and x_i represent the *i*th particle's velocity and position vectors respectively; $x_{pbest\ i}$ and x_{gbest} represent the particle's previous best value and global best value respectively; φ is a gain factor that controls the magnitude of the velocity; and ρ_1 and ρ_2 are two positive random values (Marques, *et al*., 2006). The pseudo-code that describes the selection of the best locations is listed in List. 4.

List. 4: Pseudo-code for PSO Algorithm

```
reset()
while(!found_source)
if (current_concentration > previous_concentration)
store_current_location();
store_current_concentration();
endif;

update_global_data();
find_best_global_position();

xi = update_vector() ;

move_to(xi);
endwhile;
```

A reactive obstacle avoidance method has also been implemented to avoid collision between robots and other obstacles. This method does not have any effect to the decision of the particle's target positions and only affects the path it takes to move to it.

E. Braitenberg Swarm Vehicles:

The Braitenberg vehicle is essentially a sensor-motor coupled architecture based vehicle as proposed by Valentino Braitenberg in his book Vehicles: Experiments in Synthetic Psychology (Braitenberg, 1986). The vehicles described in the book are in general reactive towards instantaneously sensed properties of their environments. This type of behavior can be observed in odor localization in nature as can be seen in the silkworm moth, the dung beetle and others(Byers, 1996; J. S. Kennedy & Marsh, 1974). Such minimalistic approach does not require long term memory thus relieving the dedication of memory resources and thus, hardware requirements.

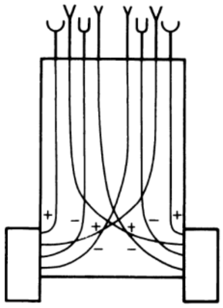

Fig. 1: Braitenberg vehicle Type 3c (Braitenberg, 1986).

Braitenberg introduces a vehicle with multiple sensors coupled to two motors, which is the type that was implemented in this research (shown in Fig. 1). This type of vehicle allows multi-sensor approach as well as provides the potential to customize sensor interfaces.

For the odor localization problem, gas sensors and wind sensors were chosen to dictate the movement of the robot. The type of configuration that was chosen was:

1) Gas sensors – *Love*
2) Wind sensors – *Aggressive*
3) Proximity, P – *Explorer*
4) Gas Attraction, A – *Explorer*

Consequently, the equations implemented to control the movement of the robot are:

$$v_r = v_{av} + k_g G_r + k_w W_l - k_p P_l - k_a A_l \quad (3)$$
$$v_l = v_{av} + k_g G_l + k_w W_r - k_p P_r - k_a A_r \quad (4)$$

where, v_{av} is the average velocity, G is the normalized gas sensor reading, W is the normalized wind sensor reading, P is the repulsion between the robots, A is the attraction between the robots when an odor trace is detected by a robot, and , k_g, k_w, $k_p$and k_a are factoring coefficients.

The wind sensor reading, W, is normalized by dividing it with the magnitude of the wind detected. Gas sensor readings are, on the other hand, normalized by using the method described by Lilienthal *et al*. as in (5) (A. J. Lilienthal & Duckett, 2003).

$$G_i = (r_i - r_{\min i})/(r_{\max i} - r_{\min i}) \quad (5)$$

where, $r_i$is the current sensor reading, $r_{min,\ i}$is the minimum sensor reading at iteration i and $r_{max,\ i}$is the minimum sensor reading at iteration i. The minimum, $r_{min,\ i}$, and maximum, $r_{max,\ i}$, sensor reading is updated dynamically in each iteration.

Instead of a typical "Mexican Hat" approach as described in previous literature (Ferri, *et al*., 2007) which is computationally heavy, a simpler version for differential wheel robots is applied based on the Braitenberg architecture. It is assumed that the robot can estimate the position of other robots relative to it, and based on that information, the value of the terms P and A is calculated and a response is created based on the information gathered. The mathematical description of the sensor response is listed below:

$$P = 1 - (d^2\theta)/({d_{\max}}^2\pi) \quad (6)$$
$$A = G\theta/\pi \quad (7)$$

where, d is the distance of the robot from the other robot, θ is the angle of the other robot from the forward axis of the robot.

V. Simulation Environment:

Simulation was run in Webots to test possible algorithms for plume tracking. It reduces development time and hardware dependency. The problem is simplified significantly as issues such as communication, sensor mounting and other hardware requirements can be ignored or simulated. Components that were simulated are the odor plume, wind, gas sensor, wind sensor, the robot, the arena, and the odor source. The following subsections will discuss about the elements that were simulated.

A. The Robot:

The robot used in the simulation is a typical differential wheel (E-Puck (Bonani *et al*., 2009)) robot mounted with two gas sensors in front and an anemometer on top. The position of the gas and wind sensors (in meters) are with respect to the robot's axis are:

Left gas sensor	: [0.04 0.06 0.04]
Right gas sensor	: [0.04 0.06 -0.04]
Wind sensor	: [0.00 0.06 0.00]

The differential wheel robot has an array of IR sensors for obstacle avoidance. As the real robot has *Zigbee* connectivity, communication is assumed to be instantaneous and reliable.

B. Test Environment:

The test area was in the simulation is an 8m by 4m arena with walls on all four sides so that it replicates the real test area where future developments will be done. There are no obstacles in the arena. Success is assumed as soon as a robot comes into 0.3m radius of the odor source.

C. Odor Plume Physics:

The odor plume is simulated based on Ferrell's model as it needs relatively low computation. Ferrell's plume model is based on the assumption that odor plumes are similar to the meandering profile of multiple filamentous entities (Ishida, *et al*., 2001). The meandering is random and follows the Gaussian distribution. This is based on previous reports on odor plume in laminar condition in which the average distribution of an odor plume fits the Gaussian distribution (Crimaldi, Wiley, & Koseff, 2002). Each filament has higher concentration in the center and is lower at the edges. Diffusion equation is used to describe the concentration in each filament.

Wind was also simulated. The wind sensor is given noise which is distributed according to Gaussian distribution. So, in a nutshell, the implemented model incorporates Advection-Diffusion with Farrell's assumption to model an odor plume in laminar flow.

VI. Results and Discussions:

In the previous research, the proposed Braitenberg algorithm was tested and found to be a feasible plume tracking strategy in single robot and multi-robot systems (Mamduh *et al*., 2013).This research compares the algorithm with other existing algorithms to gauge its performance. The optimum settings of the proposed algorithm will be used, and compared with casting, surge-spiral, surge-cast and PSO. The time for successful plume tracking and path efficiency will be analyzed.

A. Time for Successful Plume Tracking:

The time needed for successful plume tracking is useful to gauge the efficiency and the reliability of the analyzed algorithm. Table 1 summarizes the average times, $t_{avsuccess}$, and standard deviation, $\sigma_{success}$, for successful plume tracking of different single robot algorithms.

Table 1: Comparison of Average Successful Completion Time for Plume Tracking Task for Single-Robot Algorithms

Algorithm	Average Time, $t_{av\ success}$, (s)	Standard Deviation, $\sigma_{success}$, (s)
Casting	973.35	81.18
Surge-spiral	954.70	245.52
Surge-cast	856.97	167.86
Braitenberg	586.60	28.51

The results are similar to the findings of the previous research by Lochmatter *et al*. (T. Lochmatter & A. Martinoli, 2009; Lochmatter, *et al*., 2008). The recorded times are slower compared to the previous work as the robot used in their research is a Khepera III which is bigger and faster.

The worst performing algorithm is the *casting* algorithm, taking on average 973 seconds to finish the task. The zigzagging motion up the wind appears to be inefficient as the robot has to travel from one side of the plume to the other while traversing up the plume. The standard deviation however is relatively lower as it is less likely to be unable to reacquire the plume as it knows which side of the plume it is at.

Surge-spiral algorithm performs slightly better in terms of time it needs to complete the plume tracking task. The relatively long time maybe due to the fact that the robot has to traverse in a spiral path to reacquire the plume; which is highly inefficient. Furthermore, the standard deviation is worst amongst the four algorithms. The motion, although reliable in reacquiring the plume, is inefficient and depending on chance, may require an unpredictable amount of time to reacquire the plume. Nonetheless, under non-laminar conditions, the spiraling motion is expected to be a reliable strategy to reacquire the plume.

The *surge-cast* algorithm performs better than the other algorithms. However, it still lags by 270 seconds from the Braitenberg algorithm. The casting motion; when trying to find the plume even though more efficient than the spiraling motion, still causes the standard deviation to be relatively high.

The slower times of the other algorithms may be attributed to a few factors. The first is the relatively inefficient path the casting and surge-spiral algorithms take. As the algorithms move indirectly to the source of the plume, the robot traverses in a much longer path compared to the Braitenberg algorithm. The second factor is due to the fact that the rival algorithm requires the robot to turn at a spot without progressing further up the plume. The time spent in turning causes the total time needed to complete the task increase, as well as increasing the standard deviation.

Table 2: Comparison of Average Successful Completion Time for Plume Tracking Task for Multi-Robot Algorithms

Algorithm	Average Time, $t_{av\ success}$, (s)	Standard Deviation, $\sigma_{success}$, (s)	RSD (%)
PSO	699.93	69.58	9.94
Non-Cooperative	290.18	28.31	10.25
Cooperative	299.04	17.01	5.69

Table 2 summarizes the performances of PSO and the two variants of swarm Braitenberg algorithm. Both Braitenberg configurations outperform PSO in terms of average time needed for successful plume tracking, , $t_{avsuccess}$, and standard deviation, $\sigma_{success}$. The indirect path used by the entities of the PSO is a factor for its relatively slow average time. The total distance traversed by the entities is bigger than the path traversed by the both Braitenberg algorithm. As the velocities of the robots are set to be the same, PSO takes longer to finish the plume traversing path.

Considering the Relative Standard Deviation (RSD) of the three strategies, PSO and non-cooperative performs similarly. The cooperative Braitenberg algorithm has a smaller RSD again reflecting its consistency in terms of tracking the odor plume.

B. Path Efficiency:

Table 3: Comparison of Average Distance Travelled for Plume Tracking Task for Single-Robot Algorithms

Algorithm	Average Distance Travelled, d_{av} (m)	Standard Deviation, σ_d, (m)	Average Time, $t_{av\ success}$, (s)	Standard Deviation, $\sigma_{success}$, (s)
Casting	10.51	1.12	973.35	81.18
Surge-spiral	11.30	1.22	954.70	245.52
Surge-cast	8.81	0.69	856.97	167.86
Single Robot Braitenberg	9.70	0.75	586.60	28.51

Table 3 summarizes the average distances travelled by a single robot for all algorithms tested. From the results, it can be concluded that surge-cast on average takes the shortest path towards the odor source. As the robot executing this algorithm generally moves near the border of the plume in the upwind direction, which is, in geometric terms, the shortest path towards the source of a plume in laminar condition. Second best is the single robot Braitenberg algorithm. Although the robot moves straight upwind towards the plume source, this algorithm coerces the robot to move to the middle of the plume; explaining the extra distance. Casting and surge-spiral performs worse than the two said algorithms, as they take an indirect path upwind; zigzagging and spiraling respectively.

A more detailed examination of the results reveal that the average distance travelled does not agree with the average time for task completion. Even with the same average velocities, the distance and time does not seem to be correlated. The difference of approximately 1m cannot be the cause of the 270s difference between Surge-Cast and Braitenberg. This issue can be explained by looking at the strategy that is employed by the algorithms. The Braitenberg algorithm, unlike the other three single robot algorithms, constantly moves. The other algorithms require robots to turn at a spot and move in a predetermined path when it loses the plume. As such, time is wasted in these maneuvers, explaining why the Braitenberg algorithm can finish the task faster.

Considering the multi-robot algorithms as presented in Table 4, the longer time of PSO can be explained simply by the average distance travelled. PSO entities travel more than twice the distance of both multi-robot Braitenberg algorithms, and as such reflected in the average time, where it also takes more than twice the time to complete the task. Both multi-robot Braitenberg algorithms have similar average distances and time thus, performance is almost the same. However, more work needs to be done to explore the performance factors of both configurations, perhaps in the differing numbers of robots or communication reliability.

To summarize, the Braitenberg algorithm, although may not traverse the shortest path to the source, still converges the fastest. The shortest path was traversed by the surge-cast algorithm.

Table 4: Comparison of Average Distance Travelled for Plume Tracking Task for Multi-Robot Algorithms

Algorithm	Average Distance Travelled, d_{av} (m)	Standard Deviation, σ_d, (m)	Average Time, $t_{av\ success}$, (s)	Standard Deviation, $\sigma_{success}$, (s)
PSO	21.72	2.41	699.93	69.58
Non-Cooperative Braitenberg	10.78	1.06	290.18	28.31
Cooperative Braitenberg	10.56	0.98	299.04	17.01

Conclusions:

In general, the proposed algorithm was able to finish the plume tracking faster than the other algorithms compared. Furthermore, the reliability of the hybrid chemotaxis and anemotaxis configuration also outperforms the other algorithms. However, the path traversed by the surge-cast algorithm is shorter than the proposed algorithm even though the time for it to complete the task is longer. The longer average time can be attributed to the behavior of the surge-cast algorithm that requires it to spend some time in a stationary turn while switching between surging and casting.

ACKNOWLEDGEMENT

The equipment used in this project were provided by Universiti Malaysia Perlis (UniMAP). The odor plume simulation was provided by Thomas Lochmatter who is an External Lecturer in École Polytechnique Fédérale de Lausanne (EPFL), Switzerland. S. M. M. acknowledges the financial sponsorship provided by UniMAP and Ministry of Higher Education, (KPT) under the Academic Staff Training Scheme.

REFERENCES

Atema, J., 1996. Eddy Chemotaxis and Odor Landscapes: Exploration of Nature With Animal Sensors. The Biological Bulletin, 191(1): 129-138.

Bonani, M., X. Raemy, J. Pugh, F. Mondana, C. Cianci, A. Klaptocz, *et al*., 2009. The e-puck, a Robot Designed for Education in Engineering. Proceedings of the 9th Conference on Autnomous Robot Systems and Competitions, 1: 59-65.

Braitenberg, V., 1986. Vehicles: Experiments in Synthetic Psychology: Mit Press.

Byers, J.A., 1996. Temporal clumping of bark beetle arrival at pheromone traps: Modeling anemotaxis in chaotic plumes. Journal of Chemical Ecology, 22(11): 2133-2155.

Cao, Y.U., A.S. Fukunaga, A.B. Kahng, & F. Meng, 1995. Cooperative mobile robotics: antecedents and directions. Paper presented at the Intelligent Robots and Systems 95. 'Human Robot Interaction and Cooperative Robots', Proceedings. 1995 IEEE/RSJ International Conference on.

Crimaldi, J.P., M.B. Wiley, & J.R. Koseff, 2002. The relationship between mean and instantaneous structure in turbulent passive scalar plumes. Journal of Turbulence, 3(014): 1-24.

Dudek, G., M. Jenkin, E. Milios, & D. Wilkes, 1993. A taxonomy for swarm robots. Paper presented at the Intelligent Robots and Systems '93, IROS '93. Proceedings of the 1993 IEEE/RSJ International Conference on.

Dudek, G., M.M. Jenkin, E. Milios, & D. Wilkes, 1996. A taxonomy for multi-agent robotics. Autonomous Robots, 3(4): 375-397.

Dusenbery, D.B., 1989. Optimal search direction for an animal flying or swimming in a wind or current. Journal of Chemical Ecology, 15(11): 2511-2519.

Farah, A.M., & T. Duckett, 2002. Reactive Localisation of an Odour Source by a Learning Mobile Robot, In Proceedings of the Second Swedish Workshop on Autonomous Robotics., pp: 29-38.

Ferri, G., E. Caselli, V. Mattoli, A. Mondini, B. Mazzolai, & P. Dario, 2007. Explorative Particle Swarm Optimization method for gas/odor source localization in an indoor environment with no strong airflow. Paper presented at the Robotics and Biomimetics, 2007. ROBIO 2007. IEEE International Conference on.

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

Harvey, D.J., L. Tien-Fu & M.A. Keller, 2008a. Comparing Insect-Inspired Chemical Plume Tracking Algorithms Using a Mobile Robot. Robotics, IEEE Transactions on, 24(2): 307-317.

Harvey, D.J., L. Tien-Fu, & M.A. Keller, 2008b. Effectiveness of Insect-Inspired Chemical Plume-Tracking Algorithms in a Shifting Wind Field. Robotics, IEEE Transactions on, 24(1): 196-201.

Hayes, A.T., A. Martinoli, & R.M. Goodman, 2001. Swarm robotic odor localization. Paper presented at the Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on.

Hayes, A.T., A. Martinoli, & R.M. Goodman, 2002. Distributed odor source localization. Sensors Journal, IEEE, 2(3): 260-271.

Hayes, A.T., A. Martinoli, & R.M. Goodman, 2003. Swarm robotic odor localization: Off-line optimization and validation with real robots. Robotica, 21(4): 427-441.

Hernandez Bennetts, V., A.J. Lilienthal, P. Neumann, & M. Trincavelli, 2012. Mobile Robots for Localizing Gas Emission Sources on Landfill Sites: Is Bio-Inspiration the Way to Go? [Original Research]. Frontiers in Neuroengineering, 4.

Ishida, H., K. Hayashi, M. Takakusaki, T. Nakamoto, T. Moriizumi, & R. Kanzaki, 1995. Odour-source localization system mimicking behaviour of silkworm moth. Sensors and Actuators A: Physical, 51(2–3), 225-230.

Ishida, H., Y. Kagawa, T. Nakamoto, & T. Moriizumi, 1996. Odor-source localization in the clean room by an autonomous mobile sensing system. Sensors and Actuators B: Chemical, 33(1–3): 115-121.

Ishida, H., T. Nakamoto, T. Moriizumi, T. Kikas, & J. Janata, 2001. Plume-Tracking Robots: A New Application of Chemical Sensors. The Biological Bulletin, 200(2): 222-226.

Ishida, H., K. Suetsugu, T. Nakamoto, & T. Moriizumi, 1994. Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors. Sensors and Actuators A: Physical, 45(2): 153-157.

Ishida, H., H. Tanaka, H. Taniguchi, & T. Moriizumi, 2004. Mobile robot navigation using vision and olfaction to search for a gas/odor source. Paper presented at the Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on.

Ishida, H., T. Ushiku, S. Toyama, H. Taniguchi, & T. Moriizumi, 2005. Mobile robot path planning using vision and olfaction to search for a gas source. Paper presented at the Sensors, 2005 IEEE.

Ishida, H., Y. Wada & H. Matsukura, 2012. Chemical Sensing in Robotic Applications: A Review. Sensors Journal, IEEE, (99): 1-1.

Jianhua, Z., Z. Xiaojun, S. Lingyu & Z. Minglu, 2010. Basing on the olfaction and vision information fusion for robot's odor source localization. Paper presented at the Robotics and Biomimetics (ROBIO), 2010 IEEE International Conference on.

Kazadi, S., R. Goodman, D. Tsikata, D. Green & H. Lin, 2000. An Autonomous Water Vapor Plume Tracking Robot Using Passive Resistive Polymer Sensors. Autonomous Robots, 9(2): 175-188.

Kennedy, J., & R. Eberhart, 1995. Particle swarm optimization. Paper presented at the Neural Networks, 1995. Proceedings., IEEE International Conference on.

Kennedy, J.S., & D. Marsh, 1974. Pheromone-regulated anemotaxis in flying moths. Science (New York, N.Y.), 184(4140): 999-1001.

Kowadlo, G., & R.A. Russell, 2006. Using naïve physics for odor localization in a cluttered indoor environment. Autonomous Robots, 20(3): 215-230.

Kowadlo, G., & R.A. Russell, 2008. Robot odor localization: a taxonomy and survey. The International Journal of Robotics Research, 27(8): 869-894.

Li, W., J.A. Farrell, R.T. Card, & #233. 2001. Tracking of fluid-advected odor plumes: strategies inspired by insect orientation to pheromone. Adapt. Behav., 9(3-4): 143-170.

Lilienthal, A., A. Loutfi, & T. Duckett, 2006. Airborne Chemical Sensing with Mobile Robots. Sensors, 6(11): 1616-1678.

Lilienthal, A., D. Reimann, & A. Zell, 2003. Gas Source Tracing with a Mobile Robot Using an Adapted Moth Strategy, in Proceedings of Autonomous Mobile Systems, pp: 150-160.

Lilienthal, A.J., & T. Duckett, 2003. Experimental Analysis of Smelling Braitenberg Vehicles, Proceedings of the IEEE International Conference on Advanced Robotics (ICAR) pp: 375-380.

Lochmatter, T., & A. Martinoli, 2009. Theoretical analysis of three bio-inspired plume tracking algorithms. Paper presented at the Robotics and Automation, 2009. ICRA '09. IEEE International Conference on.

Lochmatter, T., & A. Martinoli, 2009. Tracking Odor Plumes in a Laminar Wind Field with Bio-inspired Algorithms. In O. Khatib, V. Kumar & G. Pappas (Eds.), Experimental Robotics., 54: 473-482): Springer Berlin Heidelberg.

Lochmatter, T., X. Raemy, L. Matthey, S. Indra, & A. Martinoli, 2008. A comparison of casting and spiraling algorithms for odor source localization in laminar flow. Paper presented at the Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on.

Loutfi, A., & S. Coradeschi, 2002. Relying on an electronic nose for odor localization. Paper presented at the Virtual and Intelligent Measurement Systems, 2002. VIMS '02. 2002 IEEE International Symposium on.

Mamduh, S.M., K. Kamarudin, S.M. Saad, A.Y.M. Shakaff, A. Zakaria, & A.H. Abdullah, 2013. Braitenberg swarm vehicles for odour plume tracking in laminar airflow. Paper presented at the Computers & Informatics (ISCI), 2013 IEEE Symposium on.

Marjovi, A., J. Nunes, P. Sousa, R. Faria & L. Marques, 2010. An olfactory-based robot swarm navigation method. Paper presented at the Robotics and Automation (ICRA), 2010 IEEE International Conference on.

Marjovi, A., & L. Marques, 2011. Multi-robot olfactory search in structured environments. Robotics and Autonomous Systems, 59(11): 867-881.

Marques, L., U. Nunes & A.T. Almeida, 2006. Particle swarm-based olfactory guided search. Autonomous Robots, 20(3): 277-287.

Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 6-15

Marques, L., U. Nunes, & A.b.T. de Almeida, 2002. Olfaction-based mobile robot navigation. Thin Solid Films, 418(1): 51-58.

Nurzaman, S.G., Y. Matsumoto, Y. Nakamura, S. Koizumi, & H. Ishiguro, 2009. Yuragi-based adaptive searching behavior in mobile robot: From bacterial chemotaxis to Levy walk. Paper presented at the Robotics and Biomimetics, 2008. ROBIO 2008. IEEE International Conference on.

Ping, J., M. Qing-Hao, & Z. Ming, 2010. Mobile robot gas source localization via top-down visual attention mechanism and shape analysis. Paper presented at the Intelligent Control and Automation (WCICA), 2010 8th World Congress on.

Ramirez, A.R.G., A.L. Lopez, A.B. Rodriguez, A.D.C. de Albornoz, & E.R. De Pieri, 2011. An infotaxis based odor navigation approach. Paper presented at the Biosignals and Biorobotics Conference (BRC), 2011 ISSNIP.

Rieser, J., A. Yonas, & K. Wikner, 1976. Radial localization of odors by human newborns. Child Dev, 47(3): 856-859.

Russell, R.A., A. Bab-Hadiashar, R.L. Shepherd, & G.G. Wallace, 2003. A comparison of reactive robot chemotaxis algorithms. Robotics and Autonomous Systems, 45(2): 83-97.

Russell, R.A., D. Thiel, R. Deveza, & A. Mackay-Sim, 1995. A robotic system to locate hazardous chemical leaks. Paper presented at the Robotics and Automation, 1995. Proceedings., 1995 IEEE International Conference on.

Sandini, G., G. Lucarini, & M. Varoli, 1993. Gradient driven self-organizing systems. Paper presented at the Intelligent Robots and Systems '93, IROS '93. Proceedings of the 1993 IEEE/RSJ International Conference on.

Wang, Y., Q.-H. Meng, & M. Zeng, 2012. Vision-Aided Spiral-Surge Algorithm for Odor Source Localization in Indoor Natural Ventilated Environments. In T. Zhang (Ed.), Mechanical Engineering and Technology, 125: 751-755): Springer Berlin Heidelberg.

Willis, M.A., 2008. Odor Plumes and Animal Orientation. In I. B. Volume Editors: Allan, K. Akimichi, M. S. Gordon, W. Gerald, D. A. Thomas, H. M. Richard, D. Peter, O. Donata, F. Stuart, K. B. Gary, M. C. Bushnell, H. K. Jon. Esther, Allan I. Basbaum (Eds.), The Senses: A Comprehensive Reference (pp. 771-781). New York: Academic Press.

Yuhua, Z., L. Dehan & C. Weihai, 2009. Swarm robotic odor source localization using ant colony algorithm. Paper presented at the Control and Automation, 2009. ICCA 2009. IEEE International Conference on.