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A Novel Bio-Controller for Localizing Pollution Sources in a Medium Peclet Environment

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Abstract

Nature inspired solutions enable biological systems to adapt and accomplish their tasks in very noisy and uncertain environments. Taking inspiration from nature, a novel bacteria controller capable of finding the source of pollution in an underwater medium turbulent environment is presented in this paper. Experiments prove that the controller is capable of performing pollution source exploration, pollution plume transverse and source declaration in a medium Peclet environment without distinctively separating these three components as most researchers did. The results obtained from these experiments are considered as a step towards the deployment of robotic fish in a highly turbulent marine environment. Finally, a brief conclusion and future extension are presented.

Keywords: bacterium inspired algorithm, environmental monitoring, robotic fish, medium Peclet environment

doi:

1 Introduction

The robots have been widely used to perform jobs that humans deem dangerous, dull and dirty. This is mostly due to their ability of high speed and high accuracy. This trend has continued into monitoring the environment and researchers are currently investigating the ways by which robots could be used to protect the environment. For example, the recent EU Shoal project aims to use a shoal of robotic fish to monitor pollution in a sea port[1]. These robotic fish will use an ad hoc network for communication within the shoal and deploy chemical sensors to find pollution sources.

Patterson *et al*. used unmanned aerial vehicles to monitor the activities of volcanoes without putting human at risk[2,3]. Furthermore, some researchers are also developing algorithms that could be used on a robot to monitor the level of radioactive or other dangerous substances in the environment[4–7]. Farrell *et al*. used an unmanned underwater vehicle to locate the source of pollution using a moth inspired algorithm and a subsumption architecture[8]. Grasso *et al*. developed a robotic lobster that can move on the sea bed and locate the source of the pollution using a crab inspired algorithm. The robotic lobster has two sensors on either side and the control algorithm works by moving the robotic lobster side to side and then moving in the direction of the antenna that has the highest reading[9–11].

Inspired by other biological organisms such as the Planarian flatworm and so on, casting behaviours have been used to control robotic platforms[12–14]. Li *et al*. for example, used the casting behaviour of the male moth to control an automated underwater vehicle in tracing a plume and subsequently finding the source of pollutants in a river with success[8]. Lilienthal *et al*. used a braitenberg vehicle to find the source of ethanol vapours in the environment[15]. Other researchers have used gradient based methods based on bacteria chemotaxis[16], while others have used multi-agent approach in finding the source[17–19].

Non-biological approaches have also being investigated. Mayhew *et al*. developed a hybrid controller and a line minimization based algorithm to find the source of a pollutant[20]. Baronov and Baillieul developed a control law that would enable them to find the source of a pollutant[21]. However, their approach requires some

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assumptions on the signal profile being covered.

In this paper, a novel bacteria controller is developed to find a pollution source in a medium Peclet number environment. Most work in this field split the task of finding the source of a plume into three stages: plume discovery, plume transversal and plume source declaration. These three stages are normally treated as separate challenges to be solved independently by various researchers[12]. However, the approach presented in this paper has the potential to incorporate these three stages into one controller without any separation. As a result, this controller could be deployed easily on a robotic fish platform for the EU shoal project.

The rest of the paper is organised as follows. Section **2** presents a bacteria controller and some modifications made to the original algorithm. The simulation and physical experiment setups are discussed in section **3**. In section **4**, some experimental results are presented to show the feasibility and performance of the proposed controller. Section **5** describes how to tune the developed controller based on the analysis of the results obtained. Finally, a brief conclusion and future work are given in section **6**.

2 Bacteria controller

The bacteria controller presented in this paper is based upon the Berg and Brown bacteria model[22]. A bacterium motion is composed of a combination of tumble and run phases. The frequency of these phases depends on the measured concentration gradient in the surrounding environment.

A run phase is generally a straight line movement and a tumble phase is a random change in direction with a mean of about 68 degrees in the *E. Coli* bacterium. If the bacterium is moving up a favourable gradient, it tumbles less and increases the length of the run phase, and vice versa if going down an unfavourable gradient. This behaviour was modelled by Berg and Brown as follows:

$$\tau = \tau_o \exp(\alpha \frac{\mathrm{d}P_b}{\mathrm{d}t}), \tag{1}$$

$$\frac{\mathrm{d}P_b}{\mathrm{d}t} = \frac{k_d}{(k_d + C)^2} \frac{\mathrm{d}C}{\mathrm{d}t}, \tag{2}$$

where τ is the mean run time and τ_o is the mean run time in the absence of concentration gradients. α is a constant of the system based on the chemotaxis sensitivity factor of the bacteria. P_b is the fraction of the receptor bound at concentration C (in this work, C was the present reading taken by the robotic agent). k_d is the dissociation constant of the bacterial chemoreceptor, $\mathrm{d}P_b/\mathrm{d}t$ is the rate of change of P_b.

However, gradient based methods do not work well in high Peclet number environments due to high disturbances in the environment[12,23]. However, marine bacteria are still able to find their food sources even in high Peclet number environments such as the ocean. They do this by using a zig-zag motion like modification to their behaviour. This behaviour becomes a control function for the agents to stay in a plume produced by a food source[24]. Barbara and Mitchell showed that the tumble frequency of the bacteria exhibiting this behaviour depends on the concentration gradient in the environment. The value of the frequency varies from specie to specie[25].

Luchsinger *et al.*[24] assumed that the ocean flow brings the bacteria close to the food source hence suggesting that bacteria have no directional steering action. However, Barbara and Mitchell argued that the bacteria are able to determine which direction the food source is and hence steer towards it. An advantage of using a bacteria model in finding a pollution source is that robot localisation in its environment is not required. This will therefore have advantages in areas of pollution where Global Positioning Satellite (GPS) signal is not readily available, especially under water environments.

2.1 Modifications to the algorithm

It was discovered from our previous work (Ref. [1]) that memory elements were used to aid the convergence of the robotic agents to a source. As a result, the version of the Berg and Brown model was used, which took the effect of the previous positions into account. This is shown in the following equations:

$$\tau = \tau_o \exp(\alpha \frac{\mathrm{d}\overline{P}_b}{\mathrm{d}t}), \tag{3}$$

$$\frac{\mathrm{d}\overline{P}_b}{\mathrm{d}t} = \tau_m^{-1} \int_{-\infty}^{t} \frac{\mathrm{d}P_b}{\mathrm{d}t'} \exp(\frac{(t'-t)}{\tau_m}) \mathrm{d}t', \tag{4}$$

where $\mathrm{d}\overline{P}_b/\mathrm{d}t$ is the weighted rate of change of P_b. τ_m is the time constant of the bacterial system.

The above equations determine the time between tumbles and hence the length of runs between tumbles.

In normal bacterium, runs could be seen as straight line motions. However, for the medium Peclet number environment, the runs were circular motions whose radius depends on the present velocity of an agent and the run time tumble length value. The velocity of the agent is adaptable and computed using Eq. (5). The circular motions had biological inspired angle step values 59 degrees ± 9 degrees, which are based upon the bacteria tracking algae[25] and are described by Eqs. (6), (7) and (8).

$$\beta = \frac{\beta_o * \upsilon_k}{C}, \tag{5}$$

$$x(t+1) = x(t) + \beta \cos \sigma(t+1), \tag{6}$$

$$y(t+1) = y(t) + \beta \sin \sigma(t+1), \tag{7}$$

$$\sigma(t+1) = \sigma(t) + 59 + rand(), \tag{8}$$

where $x(t)$, $y(t)$, $\sigma(t)$ are position and velocity of algae.

Whenever agents cannot detect any pollutant particle from the environment, the length between tumbles and hence the radius of this circular motion increases slowly until it reaches a maximum value, i.e. *MAX_VALUE*, that is defined by the user. This results in a spiral motion to increase the environment exploration when finding the plume for pollutants. Whenever a particle of pollutant is detected, this spiralling behaviour is immediately stopped. Eq. (9) describes this approach. This approach is similar to the behaviour of male moths and has been used on robotic systems (Ref. [12]).

$$\tau_c = \begin{cases} \tau_c + RES\_VALUE & \text{if} \quad C(t) = 0 \\ \tau_c = 0 & \text{if} \quad C(t) > 0 \\ \tau_c = MAX\_VALUE & \text{if} \quad \tau_c > MAX\_VALUE \end{cases}, \tag{9}$$

where *rand*() is a random number generator that generates number between 0 and 9, *MAX_VALUE* = 20 and is the highest value that τ_c can attain, *RES_VALUE* = 0.1 and is the resolution of the radius increments. During the spiralling behaviour, τ_o is updated as follows: $\tau_o = \tau_o + \tau_c$.

It must be stressed that without the spiralling feature, the proposed method still works. However its efficiency of finding plumes is reduced. By using the method above, agents are able to find the plume and trace it back to the source.

2.2 Proposed structure of our platform

Based upon our previous work[26] and the energy saving benefits of biological systems such as fish, Fig. 1 shows the robotic platform used for pollution detection in a sea port or similar environment[27].

Fig. 2 shows a cup structure formed by water flows in a river or a sea port, which is named as "shadow effect". Section **3** presents some details on how to take advantage of this cup structure on the robotic fish platform.

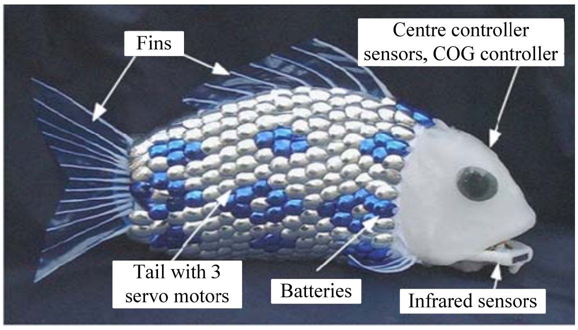

Fig. 1 A robotic fish platform at Essex[26].

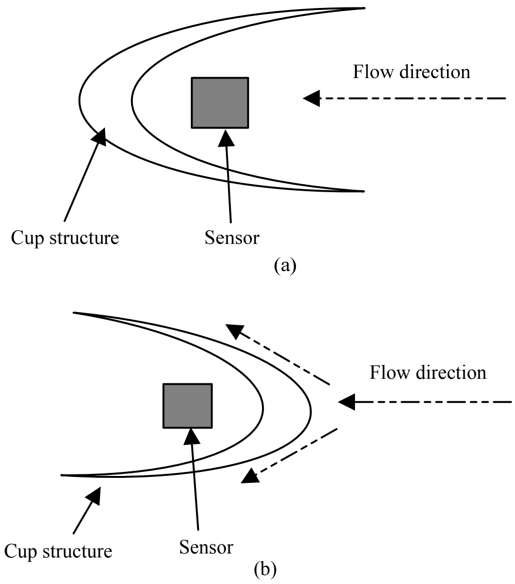

Fig. 2 (a) Sensor facing river flow and its reading increases; (b) sensor backing river flow and its reading decrease.

The cupped structure would result in agents having an increase in pollutant readings when facing the direction of the pollutant source and a decrease in pollution reading when facing away from the source. In the male moth, orientation towards the female is achieved by flying upstream into the air flow direction. Anemometric sensors and fans are often used to get the direction of air flow and to suck the air in for sampling[13,15,28]. However, these techniques increase the energy usage of systems and limit their autonomous ability due to the need to refuel more often. As we use electric batteries, energy efficiency is crucial. Hence agent structure and the scheme used to find the pollution source are also important.

3 Experimental environments

Experiments are performed using a simulated medium Peclet number environment and a physical medium Peclet number environment.

3.1 Simulated medium Peclet number environment

In order to simulate smoke, a puff model is used. It consists of particles whose number is defined by the user. The particles move randomly based upon a Gaussian distribution. As the distance from the puff release point increases, the standard deviation of each puff increases so that the structure shown in Fig. 3 is achieved. The structure of the smoke could be defined by the release rate of the puffs, the number of particles in the puff, and the standard deviation of each puff.

Assumption:

- In order to test the bacteria algorithm in a simulated medium turbulent environment, a simulated arena with a dimension of 2000 pixels by 2000 pixels is developed.
- A kinematic model is used for the simulated robots. Each robot has a dimension of 10 pixels by 10 pixels and an array of simulated chemical sensors in its center. This array of chemical sensors has a dimension of 10 pixels by 10 pixels.
- Each individual chemical sensor making up the chemical sensor array returns 1 or 0 as output. If a chemical sensor detects a pollutant particle in a location it returns 1, otherwise it returns 0.
- To measure the concentration of the pollutant in the robot position, the values of each chemical sensor in the array are added to form the total measured concentration in that location. The pollution source is located at $(x, y) = (150, 246)$ with the robot that is located at $(x, y) = (850, 246)$ at the start of the simulation.

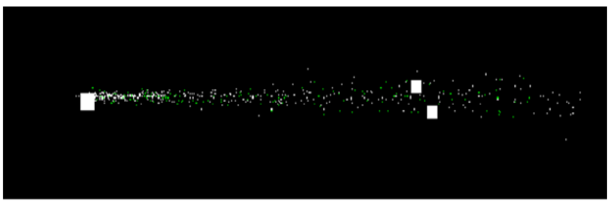

Fig. 3 Simulated medium Peclet number pollutant environment.

Other assumptions made in our experiment include:

(1) The flow velocity of the pollutant carrier does not affect the motion of a simulated robotic fish.

In practical situations, a control system could be used to stabilize the robotic fish position in the river. In order to obtain the position of the robotic fish in the river, a robotic buoy that floats on the surface and obtains GPS signals could be used to transmit information using low frequency or acoustic signals to the robotic fish under water. The time taken to send and receive the GPS data from the robotic buoy could then be used to estimate the robotic fish position in the river.

(2) The chemical sensors used in the experiment are noiseless during the simulation.

We plan to introduce noise through the use of a random number generator in subsequent experiments to investigate its effect on the algorithm. It is also assumed that there are no background noises affecting the quality of the data collected by the robotic agents.

3.2 Physical medium Peclet number environment

In order to investigate the performance of the bacteria algorithm in a medium Peclet number environment, experiments using a simulated medium turbulent pollutant are performed using the setup shown in Fig. 4. The sensor on the robotic platform is inclined at an angle of approximately 45 degrees so that it can "see" ahead and reacts.

Fig. 4 Physical medium Peclet number pollutant environment.

It was discovered in experiments that whenever the robot backs the light, its shadow is casted onto the path of the sensor. This results in a low reading to which the robot immediately responds by rotating on its axis so that turning back into the light. This effect, namely the "shadow effect", is actually very useful in re-orienting the vehicle back into the light or into the pollution flow.

This behaviour could be used to give the robot a sense of pollution direction in an underwater environment, resulting in fast localisation of the pollution source.

However, without the "shadow effect", the robot can still find the source as observed in simulation experiments in which this effect was not taken into consideration. A smoke video sequence shown in Fig. 5 was projected onto the robot arena to give a medium Peclet number pollution simulation as shown in Fig. 4. The dimensions of the arena was (x, y) = (1862, 735) in mm and the "source" of the pollutant was located at (x, y) = (503, 1077) in mm while the robot were located at about (x, y) = (1541, 1007) ± 10 in mm according to the VICON motion capturing system.

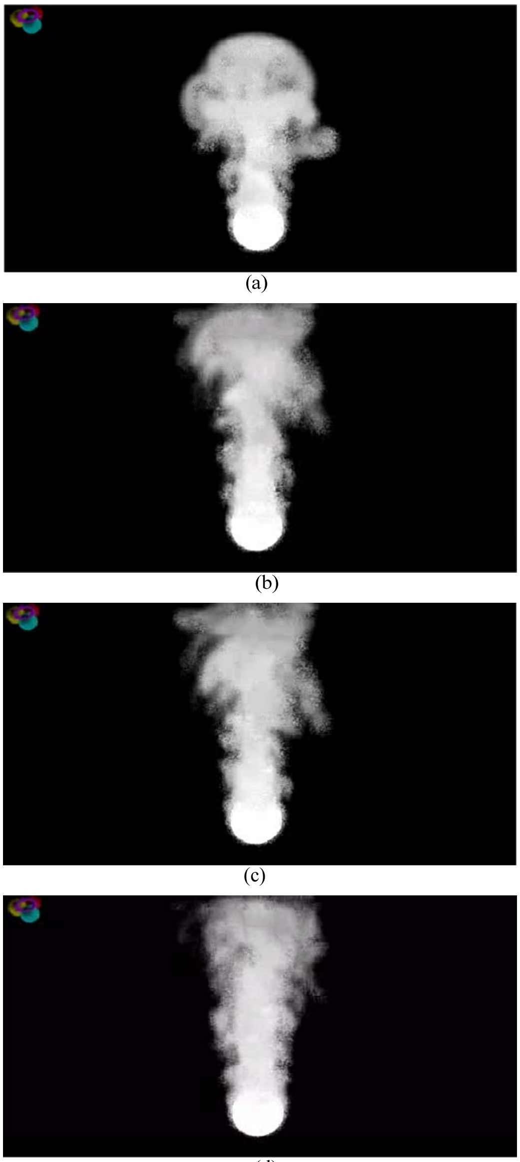

Fig. 5 Key frames of the video sequence of simulated medium Peclet number pollution.

4 Results and discussion

This section shows that it is possible to achieve deterministic behaviour of the system although the algorithm is stochastic in nature.

4.1 Simulated experiment on medium Peclet number pollutant

The robot agents used in this simulated experiment are implemented as simple kinematic point masses. Only parameters k_d and α are studied in this section because it was observed in our previous work that the τ value was used to control the exploration ability of the robot in the environment[29].

Experiments were carried out for every change in parameter values. For each value change in parameter α, changes in the value of parameter k_d are carried out from a value of 2 to 30 with increments of 2. For each value change, each experiment is running for 15 minutes. Parameter α is also incremented by 2 from a value of 2 to 30. For each of the parameter, the localisation and the plume transversal ability of the robot is studied.

4.1.1 The effect of parameter α

The localisation ability of the algorithm was studied by obtaining the number of robots that localise at the source after 15 minutes of run. An increase in α, as can be seen in Fig. 6, causes more agents to localise at the source for different k_d values.

As can be seen in Fig. 6, this effect is only very prominent at high values of k_d. At low values of k_d, more agents localise at the source in a medium turbulent environment but determinism in predicting the effect of increasing α is reduced. As a result, small values of k_d should be avoided during tuning.

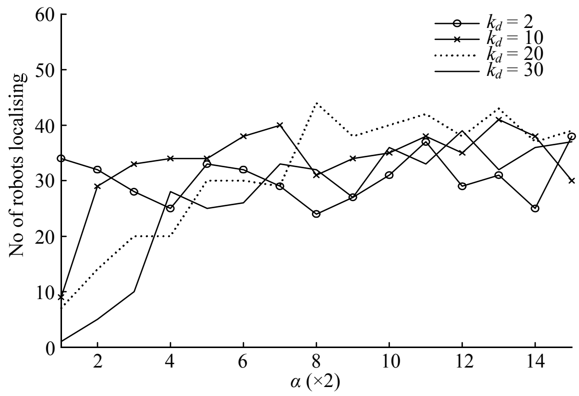

Fig. 6 Graph showing how the increase in α affects the number of robots localising at each k_d value.

The effect of α on the plume transversal ability was also studied by recording the total number of particles that the agent came into contact with in 15 minutes. Fig. 7 shows that the increase in α for each k_d results in a reduction in the number of particles that the robot comes in contact during it traveling towards the source. This is because a greater α value actually causes agents to move faster towards the source than at a lower α value.

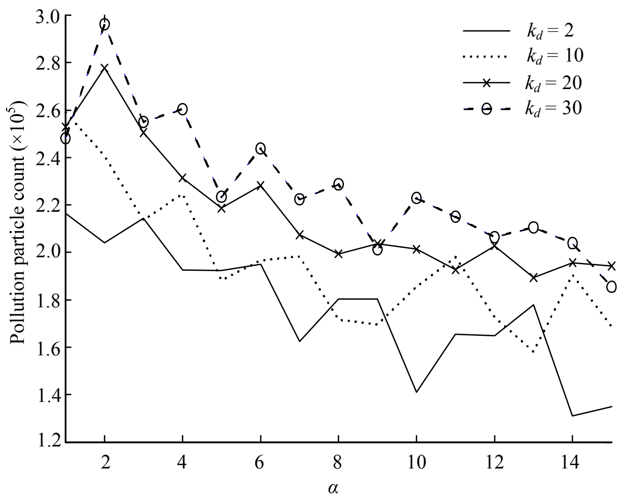

Fig. 7 Graph showing how the increase in α affects the plume transversal ability of the robots at each k_d value.

4.1.2 The effect of parameter k_d

The localisation ability of the robots under the influence of parameter k_d was also studied. Fig. 8 shows that the increase in k_d at each α value reduces the number of robots localising at the source. This is because at medium turbulent, the plume transversal ability of the robot reduces. However, the affinity of the robot to stay in the areas with pollutant particles increases, which can be seen in Fig. 9.

It can be observed much closer by plotting a Probability Density Function (PDF) of the position of agents in the cross section of the plume, as shown in Fig. 10. As can be seen, as k_d increases, the probability of the agents staying in the plume increases. It can also be seen that at a value of $k_d = 26$, the probability of the agents staying in the centre line of the plume reduces. The reason for this effect is currently under investigation. However, it could be as a result of saturation. In Fig. 3, it can be seen that the robots stopped when they reached o the source. This was an emergent behaviour observed during the experiments.

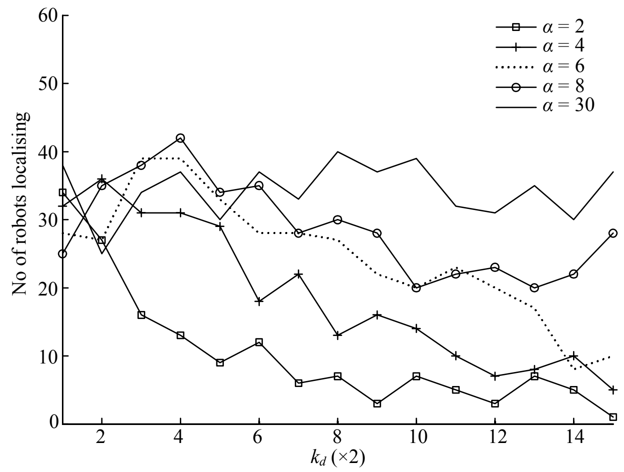

Fig. 8 Graph showing how the increase in k_d affects the number of robots localising at each α value.

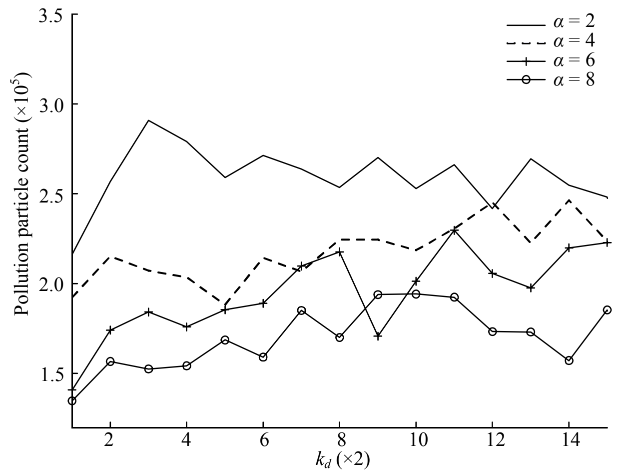

Fig. 9 Graph showing how the increase in k_d affects the plume transversal ability of the robots at each α value.

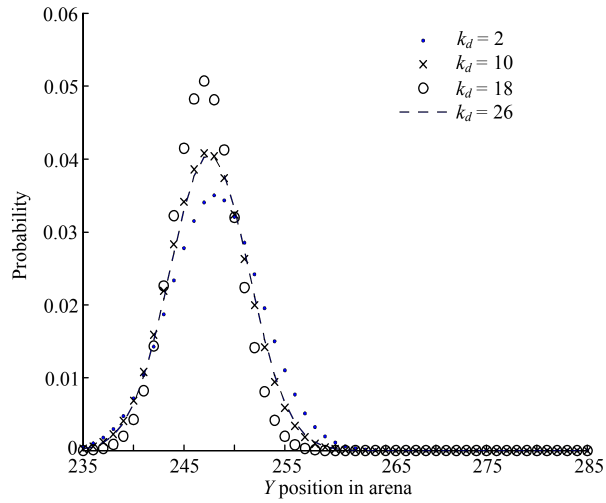

Fig. 10 The robot position distribution measured across the cross section of the plume for different k_d values.

4.2 Physical experiment on medium Peclet number pollutant

The setup for physical experiments is shown in Fig. 4. The position data of the robot is collected by using a VICON motion tracking system installed in the laboratory. The position data is used for analysis and not for the control algorithm. Furthermore, the light sensor used in this experiment did not need calibration because the bacteria control algorithm relies on a gradient based strategy. As a result, any offset in the light sensor range readings would not have a drastic effect on the bacteria control algorithm.

For every change in parameter in this section, at least 24 experiments were carried out so as to have enough test cases to understand the effect of the change in parameter. The velocity of the platform was set at 20 mm·s^{-1} to simulate Eq. (5), and was reduced as the readings was improved. A run length value of 5 was used throughout all the experiments.

The effect of α was investigated by setting $k_d = 50$ and setting α = 100, 400, 800, respectively. The results are shown in Fig. 11. It can be seen that the increase of α results in faster localisation at the source.

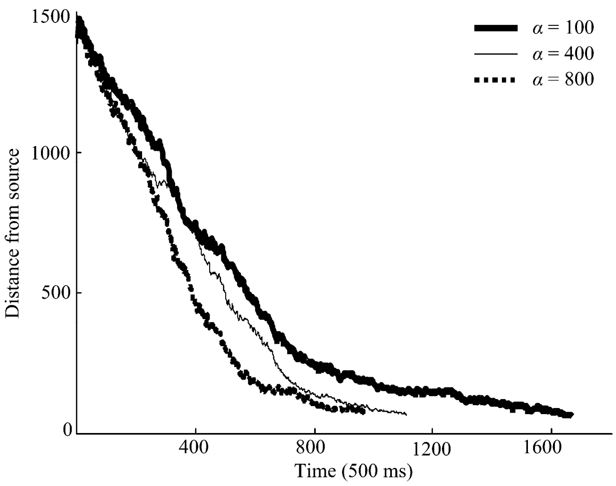

Fig. 11 The robot position distribution measured across the cross section of the plume for various chosen α value.

The effect of k_d was investigated by setting α=400 and setting k_d = 70 and 90 respectively. From simulation work in section **4.1**, it was discovered that k_d was responsible for keeping the agents in the plume. As a result, to see this clearly, Probability Density Functions (PDF) of positions covered by the robot in the arena were plotted for the two values of k_d are shown in Fig. 12.

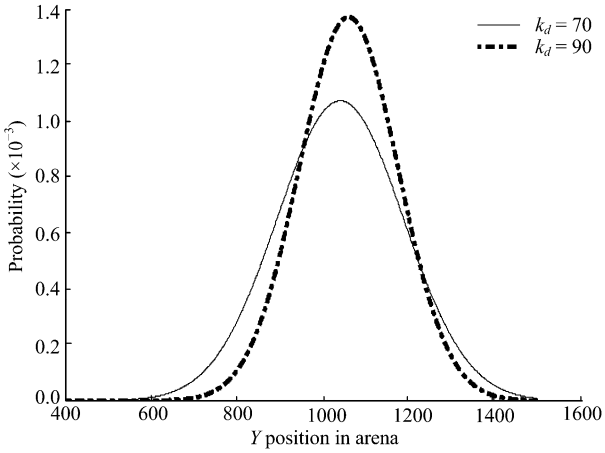

Fig. 12 The robot position distribution measured across the cross section of the plume for different k_d values.

5 Tuning the system

It can be seen from Eq. (2) that when $k_d >> C$, dP/dt = $(1/k_d)\times$dC/dt and if $k_d << C$, dP/dt =$(k_d/C^2)\times$dC/dt. Hence by increasing k_d to a large value, the motion of the agent becomes more gradient based. However, a large k_d would result in a slow progression towards the source. In order to make the agents progress towards the source, α should be increased. This in effect reduces the effect of having a large k_d. From the above, it can be concluded that a way of tuning the system would involve increasing k_d to a value to make the agents stay in the plume. Then α should be increased to enable the agents to move towards the source. τ should be adjusted according to the amount of exploration required in the environment.

If k_d, is not increased so that $k_d >> C$, the control of the agents would be based upon dP/dt = $(1/C^2)\times$dC/dt. This would result in very little control over the behaviour of the agent's motion towards the plume. Increasing α might not have much effect because of the stochastic nature of the plume.

6 Conclusion and future work

This paper has shown how the Brown and Berg bacteria controller can be used to develop a bio-controller for finding the source of pollution in a medium Peclet number environment. This controller has the ability to perform exploration for pollution sources, pollution plume transversal and pollution source declaration. It can be used effectively on a physical robotic platform in a simulated medium Peclet number environment similar to that which a robotic fish would experience in a sea port, i.e. a highly dynamic underwater environment.

In our future work, a machine learning approach such as genetic algorithm will be used to predict the source of the pollution and then subsequently reduce the time taken to localize the source. Also, the proposed algorithm will be implemented on the real robotic fish in the Gijon sea port. In addition, the proposed controller will be compared with other plume tracing methodologies in order to investigate its efficiency on solving the same problem.

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