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Exploiting Bacterial Swarms for Optimal Coverage of Dynamic Pollutant Profiles

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***Abstract*—Inspired by the simplicity of how nature solves its problems, an approach that would enable robotic agents form a visual representation of an invisible hazardous substance is presented. Such an approach would be very useful if emergency services need to systematically and strategically evacuate an area affected by invisible substance especially in a situation where evacuation resources are limited. The approach presented is computationally cheap and yet highly effective when compared to other methods such as Voronoi partitioning or simulated annealing. In addition, it does not require a polygon derived environment or a prior knowledge of the environment or pollutant and can be used to trace dynamically changing pollutant profiles. The experimental results prove that the algorithm presented in this work always converges to a pollutants distribution even though the pollutants profile is of a complex nature with no clear gradient boundaries.**

***Index Terms*—Coverage Controller, Environmental Monitoring, Flocking.**

I. Introduction

Accidentally released hazardous pollutant in the environment could cost a lot of human lives especially if the pollutant is invisible. This is because humans would not have a point of reference upon which to focus and hence avoid the approaching danger. However, by using a flock of robots, it is possible to visually represent the distribution of the invisible pollutant so that emergency services could use them as a reference upon which to systematically evacuate a city in the event of a terrorist or accidentally leak.Possessing this technology would benefit a military if their soldiers could visually see invisible dangerous substances such as radiation, nerve gas, sarin gas and so on.

However, making an invisible pollutant visible is not a trivial task. There has been a lot of research into various approaches that could be used to solve this problem such as the use of voronoi partitions, deterministic simulated annealing, artificial physics, virtual springs among others to control a group of robotic agents so that they are distributed accordingly in an environment [1][2][3][4][5][6][7][8][9][10]. Each of these approaches has its advantages and its disadvantages. Moreover, none of these approaches has been tested on dynamically changing pollutant profiles. The voronoi partition methods require a polygon derived environment to work effectively and also take a lot of computation time.

Nevertheless, Mac Schegwer et al [3]were able to implement the voronoi partition method with a Radial Basis Function (RBF) machine learning algorithm on a group of robots. The RBF was used to learn the distribution of the pollution so that they could place agents effectively in the environment whilst a ladybug exploratory behaviour was used to explore the environment in order to acquire data[11]. However, from initial study of their work, the ladybug algorithm might not be able to perform effective exploration over long distances. Shucker et al [8][12] used virtual springs to form the distribution of a pollutant by tracking points in it. Their work require long distance communication and this might not be possible when considering hardware limitations on simple robotic agents. The use of deterministic annealing as in [10] also requires a large communication burden.

Nature provides efficient and cost minimal solutions to many optimization and other engineering problems that researchers are still tying to solve. These solutions have been tested by nature over a long period of time going into million of years and have resulted in robust biological systems. As a result, this work investigates the novel possibility of combining both a flocking behaviour and a bacteria chemotaxis foraging behaviour to solve the problem of providing a visual representation of an invisible pollutant.

The aim is that the bacteria chemotaxis behaviour would provide a group of robotic agents with the means of exploring the environment whilst the flocking behaviour would enable them to move as a group and improve each others success in finding the pollutant. This technique opens up a new area of possibility in which robotic organisms are created by finding and combining various biological derived solutions in a scientific way in order to produce new hybrids capable of solving various engineering problems. This technique does not require: a polygon derived environment or a prior knowledge of the environment or pollutant.

The rest of the paper is organised as follows. Section II discusses the technical approach used in this work. In Section III, the simulation environment is discussed while section IV discusses experimental results. Section V discusses briefly how to tune the system. Finally, a brief conclusion and future work is given in Section VI.

II. Technical Approach

As mentioned above, the approach presented in this paper involves the use of a bacteria chemotaxis algorithm and a flocking algorithm. In addition to these two behaviours, a velocity function is used to make the simulated "bacteria" dwell in areas of richer food sources (or in this case higher environmental pollution concentrations). This velocity function was of the form shown in Equation 1. This velocity function was embedded in the bacteria chemotaxis algorithm.

$$\beta = \frac{\beta_o * v_k}{C} \tag{1}$$

where β is the dynamic velocity that depends on the present reading of the environmental quantity C, β_o is the standard velocity without any reading and v_k is a constant for tuning the dynamic velocity β.

A. Bacteria Chemotaxis Behaviour

There has been a lot of work in developing controllers that can find the source of pollutants. Some of them are rule based while others are derived from mathematical models[13][14] [15][16][17][18]. However, in this work, the Berg and Brown model of the bacterial chemotaxis behaviour shown in Equations 2 to 4 [19] was chosen over more complex models such as [20] because of its ease of analysis, and its ability to find the source of a pollutant using a random baised walk method. This model offers the ability to the user to control both the exploratory and exploitation behaviour of robotic agents implementing it through the tuning of its parameters.

$$\tau = \tau_o exp(\alpha \overline{\frac{dP_b}{dt}}) \tag{2}$$

$$\overline{\frac{dP_b}{dt}} = \tau_m^{-1} \int_{-\infty}^{t} \frac{dP_b}{dt'} exp(\frac{(t\prime - t)}{\tau_m}) dt\prime, \tag{3}$$

$$\frac{dP_b}{dt} = \frac{k_d}{(k_d + C)^2} \frac{dC}{dt} \tag{4}$$

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 the bacterial chemoreceptor. $\frac{dP_b}{dt}$ is the rate of change of P_b.

$\overline{\frac{dP_b}{dt}}$ is the weighted rate of change of P_b, while 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. During the tumble phase, the agent can randomly choose a range of angles in the set $\sigma\varepsilon\{0...,360\}$. The range of the angle made it possible for the robotic agents to backtrack if there was a favourable gradient behind them.

B. Flocking Behaviour:

For the flocking behaviour, a generalized Morse potential given by Equation 5 was used.

$$F_{output} = G_G * [G_R * exp(-r/20) - G_A * exp(-r/20)] \tag{5}$$

Gains of 1 for the repulsion term G_R and 0.99 for the attractant term G_A were used. It was discovered that it is possible to control how closely the agents get to each other whilst not colliding by adjusting the G_G gain.

The output from the bacteria and flocking behaviour was fused together using a linear relationship as shown in Equation 6.

$$Output = F_{output} * G_F + B_{output} * G_B \tag{6}$$

where F_{output} is the output from the flocking behaviour and B_{output} is the output from the bacteria behaviour. In this work, gains of $G_B = 0.8$ and $G_F = 0.8$ were used. In future, more intelligent ways of combining both behaviours together such as the use of fuzzy logic would be investigated.

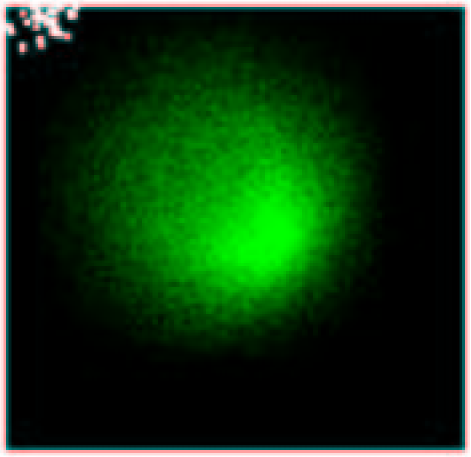
III. Simulation Setup

In order to test the effectiveness of the algorithm in visually representing a dynamically changing pollutant profile, 2000 particles were normally distributed around each of five major points. These five major points were normally distributed around the centre point of the simulated pollutant puff. By doing this, it was discovered that complex pollutant profiles could be generated. The centre point of the simulated pollutant puff was advected in x direction by moving it by 5 pixels every 16 seconds while the y direction followed the trajectory of a sine wave having an amplitude of 100 and wavelenght of 10. A kinematic model was used for the simulated robots and they each had dimensions of 10 pixels by 10 pixels and an array of simulated chemical sensors in the centre of the robot. For more information on the Simulation setup the reader is referred to [21].

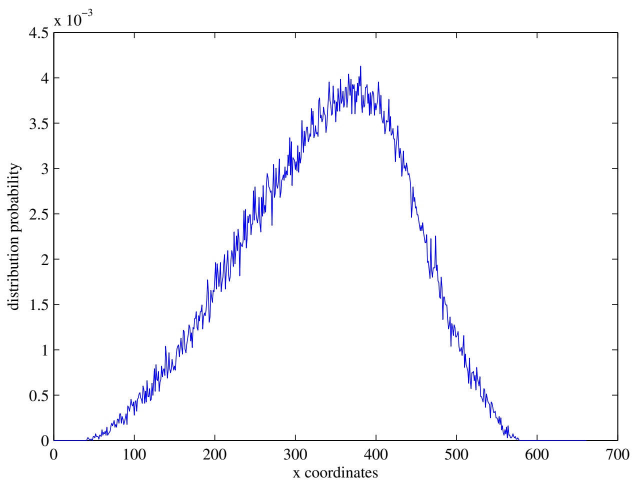
IV. Results and Discussion

A. Investigating the Bacteria Behaviour Algorithm

Before combining the flocking behaviour and the bacteria behaviour, the bacteria behaviour algorithm was studied closely. In order to study the effects of the α, K_d and the τ_o parameters of the bacteria controller on the agents, an environmental pollution with the distribution shown in Figure 1(a) and Figure 1(b) was used. This is because most pollutants in the absence of environmental disturbance a profile similar to this some time after release. This pollutant's source was at (x,y) = (400, 400) while 50 individual agents were placed at randomly generated positions at (x,y) = (50, 50) with a standard deviation of 5. For this part of the experiment, each agent did not know about the other agents and the velocity for the agents were kept constant.

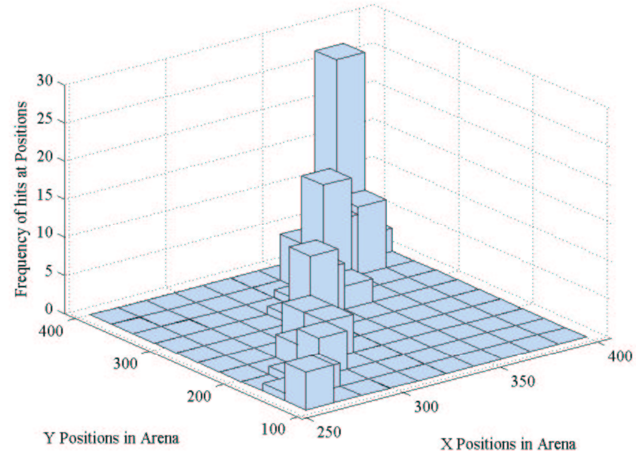


(a) Simulated Arena with pollutant

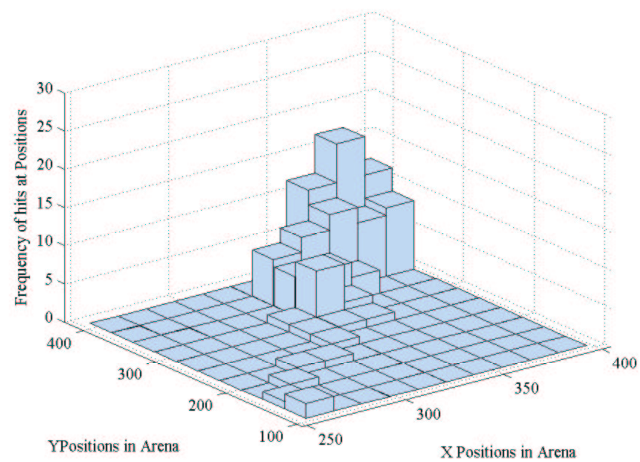


(b) Distribution of pollutant

Fig. 1. A simple generated air pollutant.



(a)



(b)

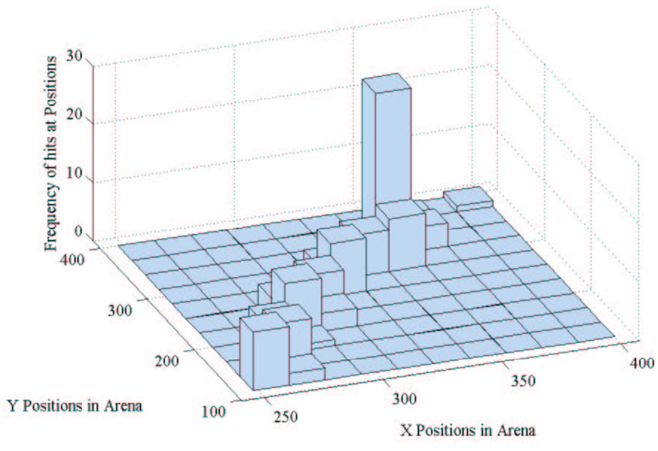
Fig. 2. Frequency of Robot Positions with different Run Length values- Fig. (a) $RunLenght$ = 2; Fig. (b) $RunLenght$ = 30.

It was discovered that the τ_o parameter controlled the exploration ability of the agent in the environment as can be seen in Figures 2(a) and 2(b) where the average position is recorded and plotted for 50 agents operating for 2.5 minutes. A higher τ_o results in more spread of the agents positions in the simulated Arena than a small τ_o.

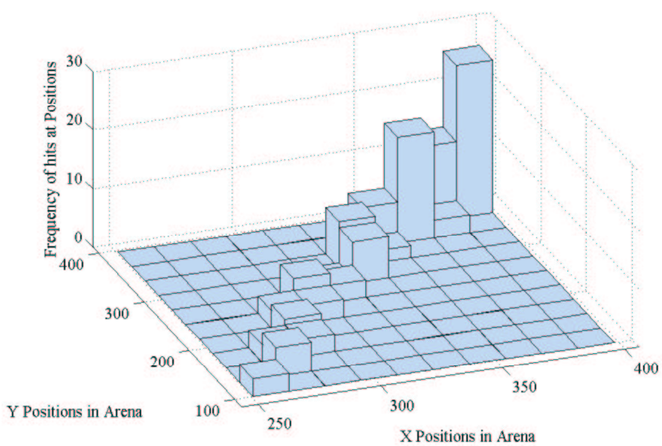
The K_d parameter controls how sensitive the agents are and their ability to stay in areas of high pollution concentrations. A higher K_d results in more agents staying the vicinity of the pollutant or in the plume generated by the pollutant than a small K_d as can be seen in Figure 3(a) and Figure 3(b). The α parameter controls the rate of descent of the agents to the source-exploitation. A higher α results in faster localization than a small α as seen in Figure 4. These parameters have to be chosen depending on the effect the user of the algorithm is trying to achieve. For explanation on how to do this and more information on the use of the bacteria behaviour algorithm for robotic control, the reader is referred to work in [22].

B. Combining the bacteria and flocking behaviour

As there is a lot of literature on the analysis of flocking behaviours, this work will now focus on the effect of combining both the bacteria and flocking behaviour together for pollution monitoring. In order to test the effectiveness of this approach, the algorithm was tested on simulated pollutant profiles that change randomly every 16 seconds as mentioned previously. The results are shown in Figure 5. By carrying out this experiment, it is was shown that the presented algorithm was capable of changing the distribution of agents according to the distribution of the pollutant in 16 seconds no matter how complex the distribution of the pollutant is.



(a)



(b)

Fig. 3. Frequency of Robot Positions with different k_d- Fig. (a) k_d = 2; Fig. (b) k_d = 30.

Moreover, the generated pollutants were composed of randomly positioned pollutant particles, did not have any smooth or clear gradient boundaries and could have many local minimums or maxima as is the case in nature. In order to further proof that this approach could form any pollutant shape, it was tested on a static box-like and doughnut-like pollutant profile as shown in Figure 6 and Figure 7. The profile in Figure 6 was generated by subtracting a smaller gaussian distribution from a larger one while the one in Figure 7 was generated from a square function. In these experiments, k_d = 2, τ_o = 2, α = 2 and v_k = 32.

V. Tuning the System

In this work, the bacteria controller was tuned so that it was able to achieve more exploitation behaviour than exploration behaviour. This made agents stay in areas that contain

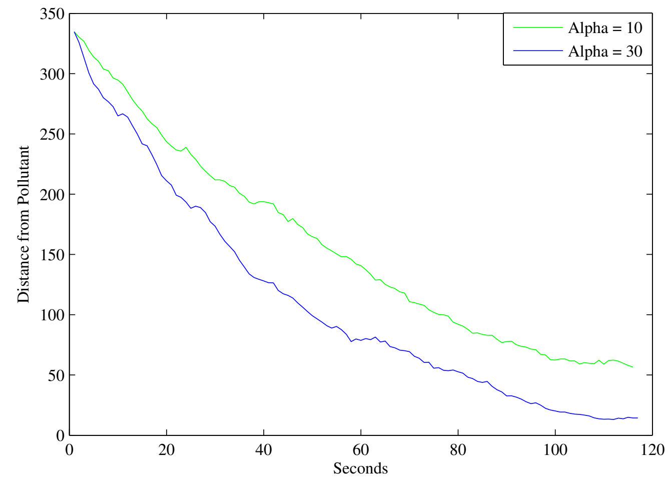


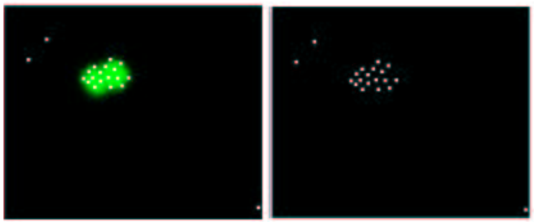
Fig. 4. Showing how α affects rate of descent of Robots.

pollution than in those areas that do not. For information on how to do this, the reader is referred to [22]. As mentioned previously, a linear Equation using the gains presented in section II was used to combine both behaviours.

It was discovered that the velocity function of Equation 1 does have a part in the optimal coverage of the pollutant's distribution. By keeping other parameters the same as the previous experiment and testing on the pollutant profile in Figure 1, a v_k value of 32 and 64 was used. It was discovered that the agents were more concentrated in the centre of the pollutant at a v_k of 64 than at a v_k of 32 in the same time period. Having the agents distributed as in Figure 9 could be fatal for humans in the sparse areas of the pollutant as it would still remain invisible to them.

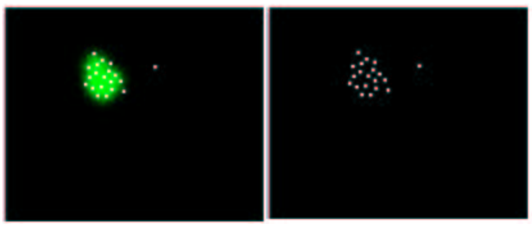
As a result, the user would either have to use a higher number of agents or specify the right v_k value to get an optimal distribution of the available agents in the pollutant. Finding the right value can be done by the use of machine learning techniques such as Genetic Algorithms. By using Genetic Algorithms, it is planned that a model based approach that makes use of Gaussian Functions would be used to approximate the distribution of the pollutant in a computationally cheap way.

This approach would have an advantage over the approach used by Schweger et al [3] in that the radius and centres of the gaussian radial basis functions would not need to be known or specified prior before runtime. Work has already begun on this with very good results. By estimating the parameters of the pollutant using model based approaches, model parameters are used as a sort of feedback mechanism to control the agents distribution in the pollutant.



(a)

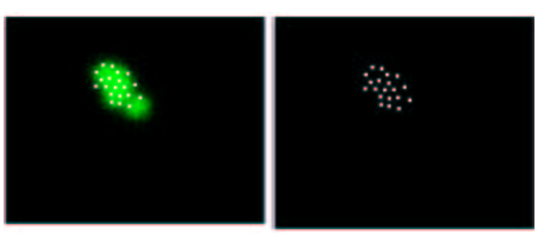
(b)



(c)

(d)

(e)



(f)

Fig. 5. Showing distribution of agents in a pollutant profile that changes every 16 seconds from t = 16s- Fig 5(a) to t = 96s - Fig 5(f).

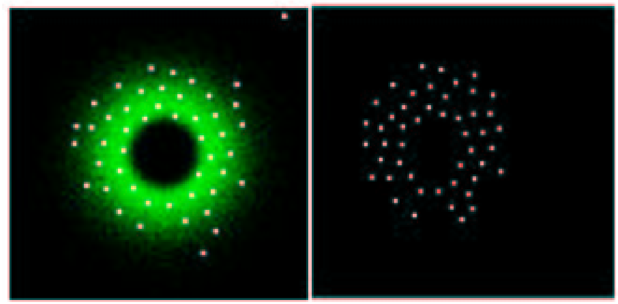


Fig. 6. Showing how the robots are distributed in a simulated doughnut profile $v_k = 16$.

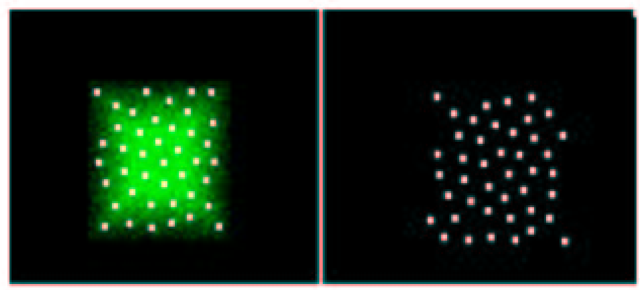


Fig. 7. Showing how the robots are distributed in a simulated Square profile.

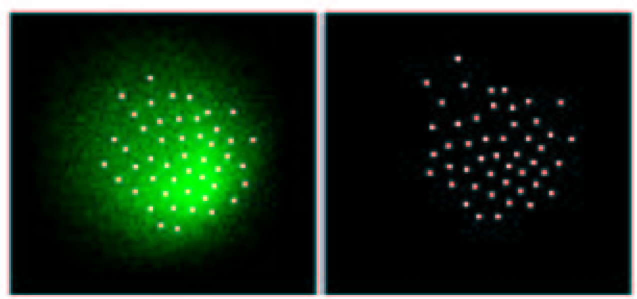


Fig. 8. Showing how the robots are distributed in a simulated skewed Gaussian profile using $v_k = 32$.

VI. Conclusion and Future Work

This paper presents an alternative method to achieve a coverage of a pollutant distribution as compared to other methods such as Voronoi partitions. The work develops a hybrid organism by combining a flocking behaviour with a bacteria foraging behaviour thereby opening up room for more novel solutions by combining solutions from different biological organisms having a sub solution to an engineering problem. The algorithm presented in this work always converges to a pollutant distribution as can be seen in the experimental section even though the pollutant's profile is of

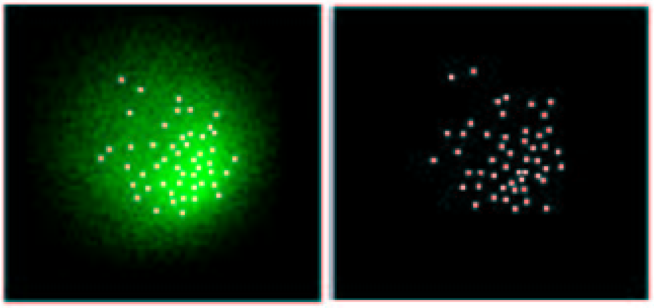


Fig. 9. Showing how the robots are distributed in a simulated skewed Gaussian profile using $v_k = 64$.

a complex nature with no clear gradient boundaries.

The approach is similar to simulated annealing in that it has a cooling function in the form of a velocity function whose parameters have to be chosen careful to get optimally distribution. Also, the distribution of agents try to reach the lowest energy difference between itself and the pollutant that is being tracked. However, the presented approach does not require a state generator for subsequent states.

Presently, a way of modifying the velocity function through learning from the environment using Genetic Algorithms is being investigated. The idea is to use Genetic Algorithms to learn a model of the pollutant and then use the learned model to modify the velocity function so that the pollutant can be optimally represented.

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