ANALYSIS OF A NOVEL CHEMOTAXIS INSPIRED LOCOMOTION STRATEGY FOR MINIATURIZED MOBILE NODES IN A HETEROGENEOUS ENVIRONMENT

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Abstract

The case for designing optimal strategies for robot locomotion has increased in significance over the past decade with the increasingly large number of unmanned mobile bots being utilized in covert operations. Furthermore, such mobile sensory nodes can be of paramount importance in conducting surveillance and rescue operations for post-disaster recovery teams. The key issue here is to design locomotion and path-planning strategies for bots such that they can operate even in regions with limited or intermittent network connectivity. In this paper, we adapt a variant of the much popular chemotaxic movement algorithm as prevalent amongst bacteria of most strains. Using such a movement strategy the bacteria gradually move towards their location, in search of food, following a chemical gradient. Suboptimal paths are periodically rejected using a process referred to as "tumbling". Using such stochastic techniques, even simplistic creatures like the bacteria reach optimal resources with little inter-communication. This paper analyses and demonstrates such a chemotaxic strategy and explains its analogical relevance in the context of target finding in miniaturized mobile sensory nodes. The paper also throws light on how future resource-aware variants of similar algorithms can be utilized to further optimize path planning strategies for such miniaturized ant-like bots.

I. INTRODUCTION

The idea of devising novel path planning strategies for mobile robots in homogenous environments and the so called "toy domains" is not unknown to us. The very idea of automating, reducing or in the least augmenting human effort through a sequence of robot-assisted tasks has been in practice for several decades now. However, the notion of exploiting the distributed knowledge base or the collective intelligence of robots to perform complex analytical tasks is relatively new. It has been increasingly observed over the past decade or so that swarm or herd behaviour in mobile robots can be exploited effectively to achieve high levels of optimality in performing difficult tasks under sever resource constraints. While swarm intelligence and the consequent particle optimization [1][2] based effort minimizing techniques are presently being utilized, similar heuristics are emerging, which show an equally promising , if not a more promising behaviour than the existing ones.

Path planning in robots is an extensively researched area with several architectures and models already being used to optimize the planned trajectory coverage and the planning time incurred. Most of these decisions fall under two major categories namely the centralized and the decentralized path planning control. The centralized control strategy, also referred to as the coupled control strategy[3], assumes the existence of a centralized control broker which collaborates between several mobile nodes and forwards control and status information amongst them[4]. The decentralized or decoupled control strategy works on a delegation-control model, wherein the task is usually delegated as a series of subtasks to the constituent nodes which perform their actions independently or with minimal dependence on any broker or each other[5][6]. Alternately, each node may try to solve the entire problem space, and thereby generate sub-optimal solutions in each iteration of its attempt. Gradually, a "decently" optimal or acceptable solution emerges as a result of this type of collaborative behaviour. It is but obvious that the decentralized technique is essentially faster than the centralized one and bypasses the dependence on a system broker, which in time-critical applications can prove to be a resource bottleneck. On the other hand, conflict resolution [7] can be a major issue in decentralized systems, when the goal conditions of one are in direct opposition with the goal conditions of another node operating in the same environment and under same resource constraints.

Such issues maybe effectively tackled using a prioritization schema[8][9] wherein each goal seeking scenario is prioritized keeping other competing scenarios in mind , and subsequently all other moving robots are treated as obstacles when compared to the primary robot in focus [10]. Furthermore, any hard quality of service (QoS) guarantees in terms of solution space traversed, time entailed in doing so and the number of dead ends reached is almost always impossible to provide in a decentralized scenario.

It is a logical implication of the centralized control technique that the controller can view the group of robots as a single composite entity and administer a global or universal path planning algorithm on that. In fact, most of the earliest known examples of path planning strategies are instances of this type [11][12]. A fair amount of literature also exists on methods to effectively combine the two approaches leading to increased QoS guarantees, better collision resolution and most importantly more scalable architectures extendible to multiple application domains. The design and construction aspects of such swarm bots are also areas of active research and interest and a fair share of literature exists for that as well[13][14][15][16].

Modern day path planning applications dwell considerably upon classical path planning algorithms making use of a number of techniques. A common method includes the use of the Laplace equation to constrain the generation of a potential function over the configuration space of end effectors. Yet another important work in this regard was done by Khatib [17] who introduced the idea of potential field method of path planning, which posited the existence of obstacles which exerted a repulsive force on the end effectors of the robot and the existence of targets or goals which exerted an attractive force on the targets. This paper offers a refreshing take on this issue of path planning and proposes a chemotaxis based locomotion strategy, a soft computing paradigm inspired from the movement of bacteria. While, the fundamental ideas of obstacles and goals are well preserved in our proposed concept, greater attention is paid towards operation under extremely constrained resources and fast goal seeking. The section 2 explains the idea of bacterial chemotaxis as observed in nature. Section 3 demonstrates the intital results achieved using our lab simulations of chemotaxic movements. Section 4 analyses the implications of the simulation results followed by section 5 which proposes a pathway for future work in this area.

II. CHEMOTAXIS IN BACTERIA

The term *taxis* refers to the migratory response of any cell to its environment. A cell responds such that it changes both its direction and the duration of the next movement step. Any tactic response on part of the cell requires some directional information from the environment that the cell may obtain by comparing any particular environmental property at multiple instances of time, i.e. the temporal gradient. If the tactic response is related to information about chemical concentrations (either attractants or repellents), it is called chemotaxis.

The phenomenon of chemotaxis is best noted amongst bacteria strain *E. coli*, one of the most intensely studied bacterial colonies in research. The sensory network of *E. coli* governs the locomotion of the bacteria towards chemical attractants and away from chemical repellents by observing temporal changes in the chemical gradient of the medium. This is achieved by the bacteria by controlling the frequency of abrupt directional changes using a phenomenon called "tumbling". A distinguishing feature of chemotaxis is that a change in the concentration of a chemical stimulant induces a rapid change in the bacteria's tumbling frequency, which gradually adapts back precisely to its pre-stimulus value after a certain temporal window [18][19]

As said, most bacterial strains bias their swimming motion towards a specific chemical and away from certain others [20]. Bacterial motion clearly resembles a random walk problem, Markov or otherwise, wherein each swimming trajectory of the bacteria is governed by a succession of random steps, each of finite duration. It would be fair to term bacterial chemotaxis as a special case of random walk or better still as a biased random walk problem, with the walk being biased by the presence of a chemical gradient. Chemotaxis in this case is achieved by modulation of the tumbling frequency. When moving in the direction of an increasing attractant concentration, the bacteria encounter a positive gradient that increases with time. In response, they tumble less frequently and thus tend to continue to move up the gradient. This process is mediated by a protein network which is also well studied in bio-chemistry domains [20][21]. We present

a model that is based on the above chemotaxis model on how distributed nodes resembling the E. coli bacteria can work in a perfectly decoupled environment and reach the food locations, which are the target locations in case of our sensory nodes, in a near optimal time. The chemotaxic algorithm we resort to in this paper is a biologically inspired optimization method inspired by Bremermann et al [22] [23] [24]. Berg and Brown [25] performed on of the first studies of chemotaxis towards amino acids of the bacterium *E. coli.* The analysis provides valuable insights and the necessary experimental parameters which we utilize in our model.

III. EXPERIMENTAL RESULTS

The idea of the initial phase of this project was to test our initial hypothesis that even in a perfectly decentralized environment with sever resource constraints, the mobile nodes or bots which are modeled as bacteria can reach their targets in a finite time with fewer nodes straying off the trajectory. The key concern here is to ensure two design goals viz.

(i)   Majority of the mobile nodes reach to within a radius 'r' of the target location within time 't', where the key objective function must minimize both 'r' and 't'.

(ii)   The distance of the remaining nodes from the desired target must also gracefully decrease with increase in the value of 't'.

We ran four sets of simulation experiments designed using MATLAB 7.10 (2010a) running on a Dell x86 based system having a dual core 2.8 GHz processor, 3GB of primary memory and 320GB of secondary memory. The four classes of simulation were modeled as follows:

Case 1: Simulating a perfect random walk problem (without food) and observing the result after 10 time-steps.

Case 2: Simulating a perfect random walk problem (without food) and observing the result after 200 time-steps.

Case 3: Simulating a "biased" random walk problem (chemotaxic, with chemical gradient) and observing the result after 10 time-steps.

Case 4: Simulating a "biased" random walk problem (chemotaxic, with chemical gradient) and observing the result after 200 time-steps.

The results of the four sets were then compared and the initial hypothesis tested for validity. The various experimental settings for the simulation were as follows:

(a)   The number of bacteria selected for migration was 100 at any instant of time.

(b)   The value of a single time step was 1 second.

(c)   The bacterial velocity is set at 0.2 cm/sec. (The experimental results show very little standard error when this value is increased or decreased i.e. the sensitivity of our final assumption is very low with respect to velocity of the cells)

(d)   Three concentration thresholds of HIGH, MEDIUM, and LOW had been set to govern the tumbling frequency with values as 0.9, 0.7 and 0.5 respectively.

The simulation results for the first case are shown in Figure 3.1. The distance measure in *X*-axis is in units of cm (distance is relative in scale to screen size of the simulation). The *Y*-axis is the number of nodes per unit area and is normalized with respect to the largest *Y* value for the given scenario. This figure shows the state of the simulation prior to introduction of a chemical gradient after a series of 10 time steps. The Figure 3.2 shows the state of the same simulation environment after a series of 200 time steps, where the inherent assumption is that no environmental parameters have been changed in the intervening period. The target in all our four simulation examples is assumed to be present at co-ordinate (0,0) and it is the objective of all the fitness functions to minimize the distance of the nodes i.e. the radium 'r' from (0,0) in the shortest possible time 't'.

Fig. 3.1 Pre-chemotaxic location chart after time step 10.

Fig. 3.2 Pre-chemotaxic location chart after time step 200.

As is expected from our hypothesis, we do observe that there is no noticeable change in the way the bacteria behave even after a difference of 180 time steps when no external gradient is provided. Thus, for a perfectly decentralized yet non-chemotaxic environment, no conclusions on time-dependency and
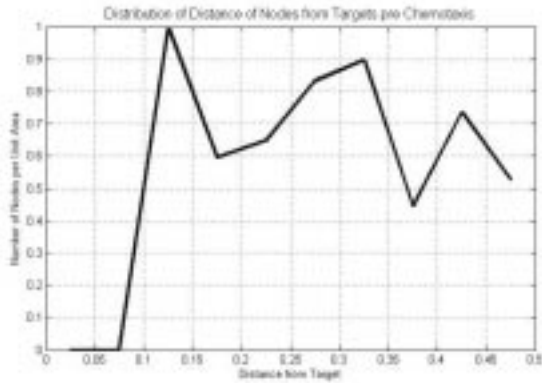
effectiveness of the algorithm can be arrived at based on our model design. Moreover, it is interesting to
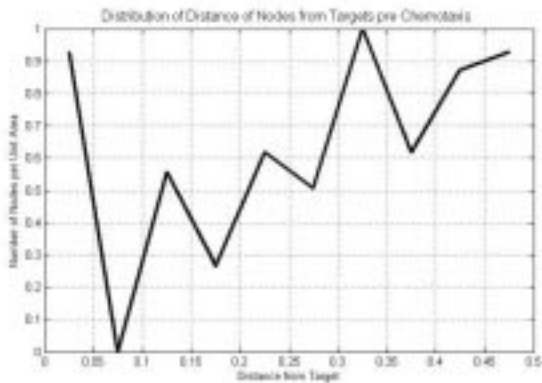
observe that almost none of the nodes actually did make it to the target even though few have reached substantially close to it. This brings out beautifully the problems arising with constrained resource problems which the sensory nodes are bound to face in a heterogeneous environment.

Next we run our second round of simulations, this time with a chemical gradient albeit a positive one in place, along with a stable policy deciding the exact tumbling threshold values, as discussed in earlier paragraphs. Once again an inherent assumptions regarding the location of the target as (0,0) and the permanence of the environmental parameters in between the time steps of the simulation is adhered to.

Figure 3.3 below demonstrates the location chart in the presence of a chemical gradient after 10 time steps while Figure 3.4 shows the location chart after 200 time steps, as in the previous simulations.

Fig. 3.3   Post-chemotaxic location chart after time step 10.

Fig. 3.4   Post-chemotaxic location chart after time step 200.

The above simulation results depict the location of the nodes in presence of the chemical gradient. The plot in Fig.3.4 confirms our hypothesis that chemical gradient indeed plays a vital role in locomotion i.e. in presence of chemotaxis, nodes are likely to reach their
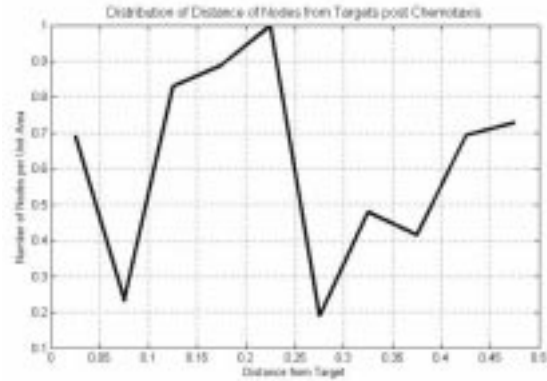
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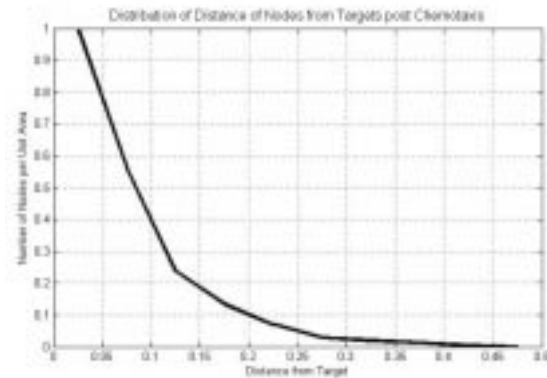
IV.   ANALYSIS OF SIMULATION RESULTS

It is but evident that our initial hypothesis stands true in the light of the initial stage simulation results as shown in Figure 3.1 – 3.4. We have conclusively proven that in presence of a positive chemical gradient or an attractant, the acceleration of the mobile nodes towards the target location gracefully increases with the reverse happening in case of a chemical repellent. Now let us turn our focus to our key design goals and see whether they have also been met or not.

Our first design goal from Section was to minimize the radius r and the time t taken by the nodes to reach within r. Judging by the simulation

results shown in Fig. 3.4, we can safely conclude that within a time $t = 20$ seconds (each time step being of 1 second duration), the nodes managed to reach within a radius of less than 0.15 cm which is impressive when compared relative to the distance scale shown in the plots. The second design goal posited that the distance of the remaining nodes from the target must also decrease gracefully with increasing time. This design goal is also clearly fulfilled as is made clear from the decreasing slope of the plot in Fig. 3.4. It is also evident from the simulation result that after a certain radius threshold of around 0.5 cm, no node will cease to exist after 't' time steps.

The implications and extensions to the chemotaxic theory that we can derive from the above conducted 2-D simulation are paramount. We observe that with increasing time 't', in a chemotaxic environment, the mean distance between the cells or nodes decrease as they tend to cluster around the target. In a resource constrained environment, this would further tend to increase competition for the already scarce resources, say bandwidth in once case. This posits the need for density-adaptive communication network setups wherein the mobile nodes as well as the intermediate network access points are power-aware and resort to hop-by-hop energy-aware routing mechanisms. Yet another conclusion of the above simulations is that, pure random walk based designs would lead to tremendous wastage of resources. Consider the location charts in Fig. 3.1 and Fig. 3.2 where the average distance of all the nodes from the target is well over 0.3 cm and would remain in the vicinity of that value for further time-steps. The bandwidth, used by these nodes, amongst other resources like power etc is essentially wasted and the network congestion caused by these mobile nodes due the inter-communicating packets would further jeopardize the resource utilization of the winning nodes nearer to the target. This is based on the assumption that all the nodes share the same intermediary public transmission network.

V. CONCLUSIONS AND FUTURE WORK

In this paper we have designed and demonstrated a path planning algorithm based on the chemotaxic movement of *E. coli* bacteria. We have successfully defended our hypothesis which argues the benefits of using a biased random-walk based architecture for perfectly decentralized nodes in a heterogeneous environment versus a pure-random walk scenario. The implications of using our model in a resource starved heterogeneous environment as one might expect in a typical surveillance or rescue operation is also well brought out in the post-simulation discussion.

In the following phases of this ongoing project we plan to deploy this locomotion strategy on low-power wireless sensor nodes (WSNs) and compare the performance of the same in a physical scenario. We are also in the process of analyzing the simulation results to find out the fitness of the model to various QoS parameters, by running t-tests and f-tests on the several different QoS hypothesis. A comparison chart with existing swarm bot path planners is also in the making at the time of writing this paper.

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