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Behavior of Artificial Bacteria

[1]K. Vijayakumari and [2] Dr. V. Baby Deepa

[1] PG and Research Department of Computer Science, Ph.D Research Scholar, Govt. Arts College, Karur

[2]PG and Research Department of Computer Science, Assistant Professor, Govt. Arts College, Karur

E-mail: [1]k.vijikumari@gmail.com, [2] deepamct@gmail.com

ABSTRACT

In a research field, Swarm intelligence is the collective behavior in swarms of insects or animals. Several algorithms are developing from such behavior to solve a huge range of complex optimization problems. In this paper, a swarm algorithm called Bacterial optimization algorithm is proposed for solving optimization tasks. Bacterial optimization techniques are proposed based on original bacterial behavior. In this behavior, accuracy and convergence speed are improved to solve the optimization problem. Its lifecycle is based on chemotaxis, communication, elimination, reproduction and migration. Chemotaxis and communication steps run for whole optimization process but others elimination, reproduction and migration run only when condition satisfied. This paper presents the behavior of E.coli bacteria and bacteria based optimization algorithm.

Keywords: Artificial bacteria, bacteria behavior, Chemotaxis and comsmunication, Reproduction and elimination, Migration.

1. INTRODUCTION

The aggregative collection of insects or animals is known as swarm behaviour. It also term as the branch of artificial intelligence. Swarm intelligence is defined by Bonbeau as ‘‘any challenge to propose algorithms to solve problems inspired by the collective behaviour of the social insect colonies and other animal societies” [13]. The self-organization and labor division are the key components of swarm intelligence. Some advantages of Swarm intelligence such as scalability, fault tolerance, adaptation, speed, modularity, autonomy and parallelism [14]. In Recent years, nature inspired optimization technique has attracted many researchers like Particle swarm optimization [6] it based on the behaviour of bird flocking or fish schooling, ant colony optimization [4] it based on the behaviour of ants and bee algorithm based on honey bee are simulated by natural swarm organisms [5].

Although PSO and ABC are the most popular swarm algorithms for solving complex optimization problems, they present serious flaws such as premature convergence and difficulty to overcome local minima [15, 16]. Nowadays Bacterial based algorithm is mostly used to solve the real world problems like PID Controller [1], Machine learning [2] and so on. Bacterial algorithm based on foraging behavior of Escherichia coli bacteria (Passino, 2002). The main idea of this behavior is to find a maximum nutrition in a particular time. Bacterial based algorithm mainly considers the behavior of bacteria [7].

The E. Coli bacterium has a plasma membrane, cell wall, and capsule that contains the cytoplasm and nucleoid [3]. E. Coli grows, it gets long and then divides into two “daughters.” If it take sufficient food and keep at the temperature of the human gut of 37°C,E. Coli can reproduce itself and take a copy of itself in about 20 min; hence increase of a bacteria is exponential with a comparatively short time to double.

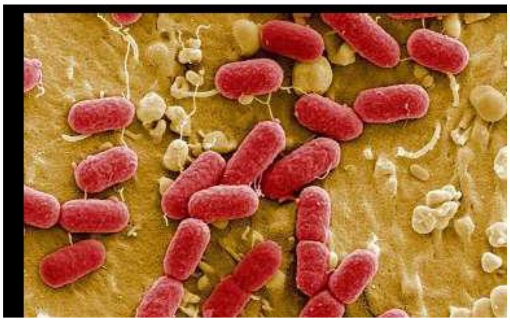

Fig 1 E.coli bacteria

The E.Coli bacterium has a control system that enables it to search for food and try to avoid harmful substances. For example, it swims away from alkaline and acidic environments and toward more neutral ones.

1.1 Behavior of Artificial Bacteria:

Artificial bacteria behavior divided into five parts: Chemotaxis, Elimination, Reproduction, Migration and Communication [8]. Bacteria can swim and tumble in cell wall (Fig 2 (a)). After sometime the bacteria that have best fitness value it will survive others will get eliminated. The survived bacteria can generate new offspring’s (Fig 2 (b)). If there is no resources for survived bacteria it may choose to migrate to new better nutrition position (Fig 2 (c)). During searching for better nutrition information sharing and self experience are essential. This process brings together the macro- and the micro scale that allows bacteria to make chemotaxis movements as well as interacting with other bacterium. This can be appreciated by incorporating the method of chemotaxis and communication into the complete optimization process.

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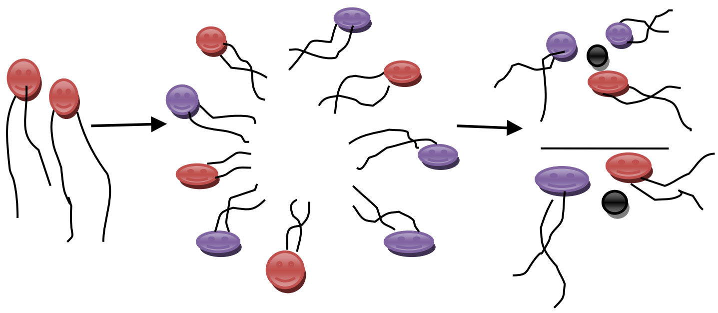


Fig 2: Artificial bacteria individual and social behavior

1.2 Principle:

Chemotaxis and communication are merged together for whole optimization process [1]. After long process of chemotaxis and communication model bacteria may die for lack of food or it reproduce [10,11]. In the complicated environment some bacteria may go out of boundary, for this reason in bacteria life cycle migration perform as an independent model it involves energy depletion, group diversity and chemotaxis efficiency [2]. The bacteria life cycle is shown in Fig 3.

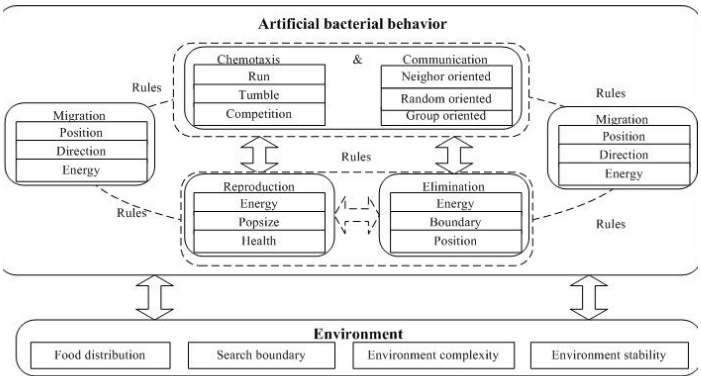


Fig 3 Bacteria life cycle

1.3 Chemotaxis and communication model:

In this phase bacteria trying to find wealthy nutrition, if it find good nutrition it will keep on swimming in same direction otherwise it will tumble to change current direction. Chemotaxis combined with communication for whole optimization process. The important phases in chemotaxis operation is Tumbling, moving and swimming [9]. In the process of running, all flagella turn counterclockwise to form a dense propelling the cell along a helical trajectory. In this way, bacteria can swim straightly in one direction. In the case of tumbling, the flagella rotate clockwise, which pull the bacterium in different directions. Fig 4 represent the structure of chemotaxis and it directed by three elements: group information, personal previous information, and a random direction. These refer running and tumbling bacteria moves toward optimum solution.

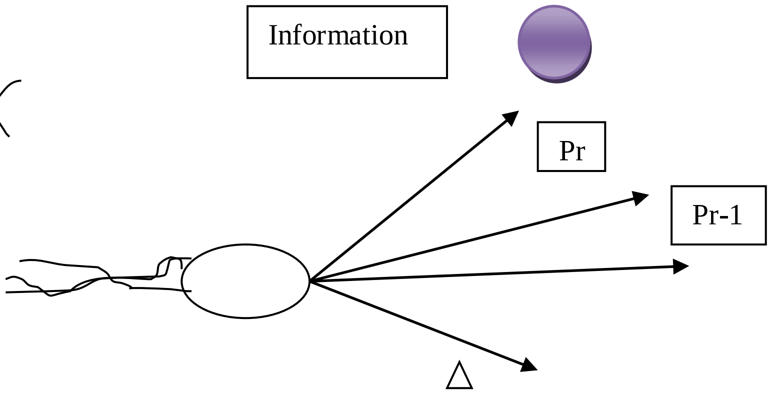
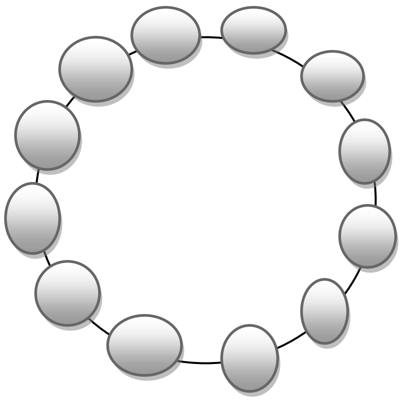
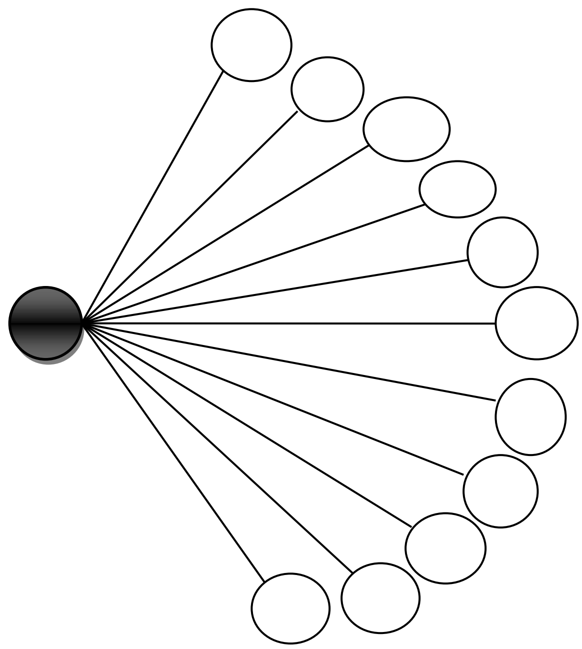


Fig 4: Chemotaxis

It represents three types of structures [8]. Dynamic neighbor oriented fig 5(a), random oriented fig 5 (b) and group oriented fig 5 (c). In Dynamic and random, individuals share the information between two and in group mechanism, bacteria communicate if it in group.



(a) Dynamic neighbour oriented



(b) Random oriented

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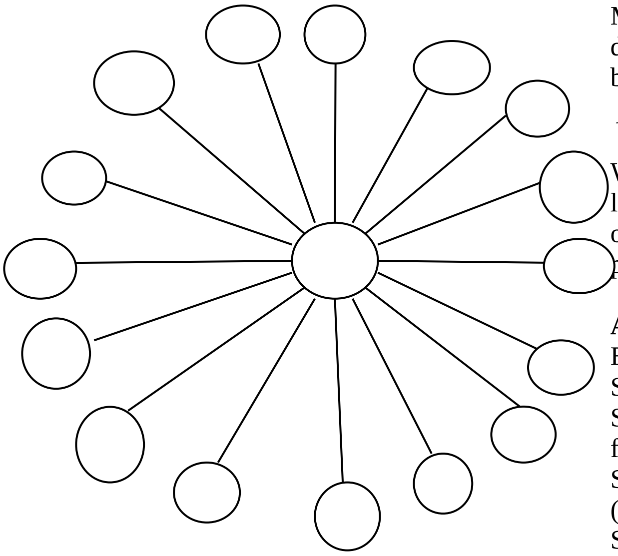

(c) Group oriented

Fig 5: Communication mechanism

Algorithm for individual exchange
Begin
Step 1: For each bacterium

Step 2: Given probability greater than random then share the information with two bacteria

Step 3: otherwise choose two random bacteria, share the information with those random bacteria

End

Formula for communication process:

$$Position_i(T) = Position_i(T-1) + R_i.(Run_{\inf o}) + R\Delta(i) \quad (1)$$

$$Position_i(T) = Position_i(T-1) + R_i.(Tumb_{\inf o}) + R\Delta(i) \quad (2)$$

It's for updating the position to consider the group and individual relationship.

1.4 Elimination and Reproduction model:

According to natural selection, if bacteria have low search ability it have chance to eliminate. Those who perform well in chemotaxis it have more chance to survive. Each bacterium has certain degree based on the rich nutrition and search capabilities. If the degree is high means it has rich nutrition and better search capabilities. According to this elimination and reproduction model will executed. It calculated by the formula given below,

$$\begin{aligned} &if\ L_i > L_{given}\ and\ i \in healthy,\ then\ i \in Candidate_{repr} \\ &if\ L_i < L_{given}\ and\ i \in healthy,\ then\ i \in Candidate_{eli} \\ &if\ i \in unhealthy, \qquad then\ i \in Candidate_{eli} \end{aligned} \quad (3)$$

Where, L_i -is the energy level of i^{th} bacterial colony. For all bacteria the behavior must be restricted to certain area. In general, individuals may not allowed to go out the certain area, if bacteria move out of the region means it perform two steps, one is to change the forward direction and another one is to generate new individuals .

1.5 Migration model:

In migration model, bacteria can yield more nutrition [12]. Migration of bacteria not depends upon certain probabilities it depends upon certain conditions. If the condition is satisfied bacteria would move to new random place as described below,

$$Position_i(T) = rand.(ub - lb) + lb \quad (4)$$

Where rand denotes random number between 0 and 1, lb means lower boundary and ub means upper boundary. As per optimization concept, migration model can avoid local optimum problem.

Algorithm for migration model:
Begin
Step 1: For each bacterium
Step 2: if rules is satisfied then migrate to new position by formula (4)
Step 3: else it perform chemotaxis model using formula (1) and (2)
Step 4: If terminating condition is not satisfied, then go to step2.
End

2. Implementation of Chemotaxis and Communication:

As illustrated above, bacteria chemotaxis life time can be divided into two models: tumbling and swimming. In the process of tumbling, a stochastic direction participates into actually swimming process. Therefore, turbulent director and optimal searching director altogether influence the search orientation in tumbling, update the positions of each bacterium as 5, whereas no turbulent director acceding in swimming process to affect the bacteria swimming toward optimal as 6 formulated:

Therefore, the updating the position of the each bacterial colony as follows,

$$\begin{aligned} Position_i(T) = {} & Position_i(T-1) + C(i) \\ & *[f_i.(G_{best} - Position_i(T-1)) + (1-f_i) \\ & *(P_{best_i} - Position_i(T-1)) + turb_i] \end{aligned} \quad (5)$$

$$\begin{aligned} Position_i(T) = {} & Position_i(T-1) + C(i) \\ & *[f_i.(G_{best} - Position_i(T-1)) + (1-f_i) \\ & *(P_{best_i} - Position_i(T-1))] \end{aligned} \quad (6)$$

$$C(i) = C_{\min} + \left(\frac{Iter_{\max} - Iter_j}{Iter_{\max}} \right).(C_{\max} - C_{\min}) \quad (18)$$

Where, $turb_i$ denotes the turbulent direction variance of the i^{th} bacterial colony, $C(i)$ - is the chemotaxis step size of the i^{th} bacterial colony, $f_i \in (0,1)$, G_{best} is the global best and P_{best} is the personal best of the i^{th} bacterial colony. $Iter_{\max}$, $Iter_j$ are the maximum iteration and current iteration respectively.

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3. CONCLUSION

To enhance the global search behavior in swarm intelligent family, bacterial based algorithm shows the better result. In this paper bacterial optimization algorithm has been discussed. The bacteria are treated with agent of swarm intelligence. The communication capability is one of main aspect of group intelligence. Additionally, reproduction, migration and elimination are optimization strategies in bacterial algorithm. Many researchers prove that this algorithm improves the convergence speed and precision. Here we presented the basic behavior of bacterial colony optimization.

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