Volume 4, Issue 6, June 2014 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Survey on Bio-Inspired Techniques in WSN

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Abstract— WSN monitors an environment by sensing its physical properties. It is a network of tiny, inexpensive autonomous nodes that can acquire process and transmit sensory data over wireless medium. One or more powerful base stations serve as the final destination of the data. The properties of WSNs that pose technical challenges include dense ad-hoc deployment, dynamic topology, and spatial distribution and constrains in bandwidth, memory, computational resources and energy. WSN issues such as node deployment, localization, energy-aware clustering and data-aggregation are often formulated as optimization problems. Traditional analytical optimization techniques require enormous computational efforts, which grow exponentially as the problem size increases. An optimization method that requires moderate memory and computational resources and yet produces good results is desirable, especially for implementation on an individual sensor node. Bio-inspired optimization methods are computationally efficient alternatives to analytical methods. This paper explains the different bio-inspired techniques that are use in wireless sensor network.

Keywords— Wireless Sensor Network, Swarm Intelligence, Ant Colony Optimization, PSO, BFA.

I. INTRODUCTION

After a decade of bio-inspired networking research, we see many very successful application examples that either directly improve specific networking-related operations or simply foster novel research projects to reinvestigate what we thought of being common knowledge in engineering. In fact, when we look carefully into nature, it is clearly observed that the dynamics of many biological systems and laws governing them are based on a surprisingly small number of simple generic rules which yield collaborative yet effective patterns for resource management and task allocation, social differentiation, synchronization (or de-synchronization) without the need for any externally controlling entity. For example, by means of these capabilities, billions of blood cells which constitute the immune system can protect an organism from pathogens without any central control of the brain [1]. Similarly, an entire organism is autonomously maintained in a relatively stable equilibrium state via a major functionality, i.e., homeostasis, for the operation of vital functions without any need for a central biological controller [2]. The task allocation process in the insect colonies is collaboratively decided and performed according to the willingness of an individual such that the overall task is optimized with a global intelligence comprised of simple individual responses [3].

At the same time, communication and management aspects in networking are becoming even more challenging in future networking domains ranging from nanoscale communication networks [4] to Interplanetary Internet [5]. Technical challenges include the management of thousands and millions of inter-networking devices that have to be organized using scare resources and disruptive communication channels. In spite of these limitations, the networking community is developing astonishing technical solutions, in many cases inspired by self organization mechanisms inherently existing in Nature.

Three main areas of bio-inspired research can be distinguished:

Bio-inspired computing represents a class of algorithms focusing on efficient computing, e.g., for optimization processes and pattern recognition.

Bio-inspired systems constitute a class of system architectures for massively distributed and collaborative systems, e.g., for distributed sensing and exploration.

Bio-inspired networking is a class of strategies for efficient and scalable networking under uncertain conditions, e.g., for autonomic organization in largely distributed systems.

II. APPROACHES TO BIO-INSPIRED NETWORKING

In this section, we introduce the current state-of-the-art in bio-inspired networking. However, we selected a number of techniques and methods for more detailed presentation that clearly show advantages in fields of communication networks. In the discussion, we try to highlight the necessary modelling of biological phenomena or principles and their application in networking [6].

A. SWARM INTELLIGENCE:-

The behavior of large groups of interacting small insects such as ants and bees builds the basis for the field of swarm intelligence. Simple and seemingly unrelated, autonomously working individuals are considered to compose complex cooperative tasks. Similar actions are required in various areas of engineering and computer science. Thus, swarm intelligence is forming a basis for building self-organizing systems. The main focus lies on the formation of groups or clusters that allow efficient task allocation mechanisms. Successful application of swarm intelligence methods has been demonstrated in task allocation and control of multi-robot systems [3]. In many cases, direct communication among individual insects is exploited, e.g., in the case of dancing bees. However, especially the stigmergic communication via changes in the environment is as fascinating as helpful to coordinate massively distributed systems. The difference between the ‘‘wireless” network of an insect population and an engineered wireless sensor network is that insects encode messages with semiochemicals (also known as infochemicals) rather than with radio frequencies. Application examples of the bees' dance range from routing to intruder detection [6].

1) *PSO in WSNs:*

Particle Swarm Optimization (PSO) was invented by Kennedy and Eberhart in 1995 [7,8]. They were trying to simulate the amazing controlled motion of a swarm of birds flying in one direction. In PSO, particles regulate their information (flying directions) with its own flying experience as well as their neighbors flying experience. In a word it combines self-experience with social experience, so t he basic PSO was a social behavior simulator. It consists of a swarm of s candidate solutions called particles. Several revised versions of PSO have emerged with a range of concepts and applications including WSNs. A number of parameters such as inertia weight (w) and confidence factors (c1, c2) were added later on to improve the efficiency of the method. After several improvement processes it was understood that the technique can be used as a population -based optimizer and it can solve stochastic nonlinear optimization problems in a cheaper way [7].

Generating particles' position and velocities, velocity update, and position update- these three main steps defines the PSO algorithm. Here particle refers to a point in a D -dimensional search space that updates its position from one point to another based on related velocity updates. The i-th individual (particle) of the population, which is called swarm, can be represented in a D -dimensional vector as$X_i = X_{i1}X_{i2} \ldots\ldots X_{iD}$. The velocity or the position change for particle i is represented as $V_i = V_{i1}V_{i2} \ldots\ldots V_{iD}$ and the best previously visited position of this particle is denoted as $P_i = P_{i1}P_{i2} \ldots\ldots P_{iD}$. Symbol represents the best particle in the swarm and w is the inertia weight. The particles are then manipulated according to the following two equations:

$$V_{id}^{n+1} = wV_{id}^{n+1} + c_1 r_1^n (P_{id}^n - X_{id}^n) + c_2 r_2^n \left(P_{gd}^n - X_{id}^n\right) \ (1)$$

$$X_{id}^{n+1} = X_{id}^{n+1} + V_{id}^{n+1} \ (2)$$

Where d = 1, 2, ..., D, i = 1, 2, ..., N and N is the size of the swarm and n = 1, 2, ... denotes the iteration number. Two random numbers r1, r2 which are uniformly distributed in [0, 1] ensure good coverage. They also ensure the avoidance of falling into local optima which was a problem of the classical approaches. The inertia weight w manipulates the trade-off between exploration and exploitation abilities of the flying points. Another two important parameters are c1 (self-confidence factor) and c2 (swarm confidence factor). The stopping criterion of the algorithm depends solely on which type of problem it‘s going to deal with. One of the problems of PSO is the tendency towards a fast and premature convergence in mid-optimum points. A lot of effort has been made so far to solve this problem [7].

2) *Ant Colony Optimization*

ACO is among the most successful swarm based algorithms proposed by Dorigo & Di Caro in 1992[9, 10], It is a probabilistic method for solving computational problems, which can be reduced to find good paths through graphs It is inspired by the behavior of ants in finding paths from the colony to the food. In the real World, ants initially wander randomly, after finding food, they return to their colony while laying down pheromone trails. If other ants find such a path, they do not keep traveling at random, but rather follow the trail, returning and reinforcing it if they eventually find food. However, the pheromone trail starts to evaporate over time, therefore reducing its attractive strength. More the time to travel down and back again for ant, more will be evaporation of pheromones. A short path, by comparison, gets marched over faster, and thus the pheromone density remains high as it is laid on the path as fast as it can evaporate. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained. Thus, when one ant finds a short path from the colony to a food source (i.e., a good solution), other ants are more likely to follow that path, and positive feedback eventually leaves all the ants following a single path [9].

3) *Bacterial Foraging Algorithm*

BFA is a newly introduced evolutionary optimization algorithm that mimics the foraging behavior of Escherichia coli (commonly referred to as E. coli) bacteria. [11] There are successful applications of BFA in optimization problems, such as economic load dispatch and power systems. BFA models the movement of E. coli bacteria that thrive to find nutrient-rich locations in human intestine. An E. coli bacterium moves using a pattern of two types of movements: tumbling and swimming. Tumbling refers to a random change in the direction of movement, and swimming refers to moving in a straight line in a given direction. A bacterium in a neutral medium alternates between tumbling and swimming movements [11].

4) Artificial Bee Colony Algorithm

These algorithms are inspired by the behavior of bees in nature which are classified into two; foraging behavior & mating behavior [9]. Algorithm simulating foraging behavior of the bees, proposed by Karaboga and Basturk [12] includes artificial bee colony (ABC), the virtual Bee algorithm, the bee colony optimization algorithm, Bee hive algorithm. In the Bee swarm optimization algorithm an individual entity exhibit a simple set of behavior policies, but a group entity shows complex evolving behavior with useful properties such as scalability and adaptability.

In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making a decision to choose a food source is called on looker and one going to the food source visited by it before is named employed bee. The scout bee is the kind of bee that carries out random search for new sources. The location of food source corresponds to a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality of the solution [9].

An employed bee produces a modification on the position in her memory depending on the local information and tests the nectar amount (fitness value) of the new source (new solution). Provided that the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. After all employed bees complete the search process; they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. The global search performance of the algorithm depends on random search process performed by scouts and neighbor solution production mechanism performed by employed and onlooker bees [9].

5) Artificial Immune System

Artificial Immune algorithm [14] is based on clonal selection principle and is a population based algorithm. The AIS is inspired by the human immune system which is a highly evolved, parallel and distributed adaptive system that exhibits the strengths like: immune recognition, reinforcement learning, feature extraction, immune memory, diversity and robustness. The mutation operator is the efficiency deciding factor of this technique. The steps in AIS are as follows [9]:

Initialization of antibodies (potential solutions to the problem). Antigens represent the value of the objective function f(x) to be optimized.

Cloning, determines the resemblance or fitness of each antibody. Based on this fitness the antibodies are cloned which means the best antibodies are cloned mostly.

Hyper mutation: The clones are then undergoes to a hyper mutation process in which the clones are mutated in inverse proportion to their affinity. The clones are then evaluated along with their original antibodies out of which the best N antibodies are selected for the next iteration [9].

6) Cellular signaling networks

Basically, the term signaling describes the interactions between single signaling molecules. Such communication, also known as signaling pathways, is an example for very efficient and specific communication. Cellular signaling occurs at multiple levels and in many shapes. Briefly, cellular interactions can be viewed as processing in two steps. Initially, an extracellular molecule binds to a specific receptor on a target cell, converting the dormant receptor to an active state. Subsequently, the receptor stimulates intracellular biochemical pathways leading to a cellular response [6]. In general, the following two cellular signaling techniques can be distinguished [13]:

Intracellular signaling – The signal from the extracellular source is transferred through the cell membrane. Inside of the target cell, complex signaling cascades are involved in the information transfer (signal transduction), which finally result in gene expression or an alteration in enzyme activity and, therefore, define the cellular response.

Intercellular signaling – Cells can communicate via cell surface molecules. In this process, a surface molecule of one cell or even a soluble molecule, which is released by one cell, directly binds to a specific receptor molecule on another cell. Soluble molecules such as hormones can also be transported via the blood to remote locations.

III. CONCLUSIONS

Wireless sensor networks (WSNs) are networks of autonomous nodes used for monitoring an environment. Developers of WSNs face challenges that arise from communication link failures, memory and computational constraints, and limited energy. Many issues in WSNs are formulated as multidimensional optimization problems, and approached through bio-inspired techniques. Bio inspired principles have found their way into network node design and research due to the appealing analogies between biological systems and large networks of small sensors. This paper provides an overview of bio inspired methods such as swarm intelligence, artificial immune system exchange applicable for sensor network design.

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