A SURVEY ON LEARNING AUTOMATA BASED ALGORITHMS AND ITS APPROACHES IN WIRELESS SENSOR NETWORKS

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Abstract

The protocols in designed for Wireless Sensor Networks (WSN) have a unique requirement for being of low complexity and energy-efficient. Due to their possible deployment in remote locations for civil, educational, scientific, and military purposes, security, which includes intrusion detection and intrusion prevention, is of utmost importance. Several algorithms have already been provided for problems of data aggregation in wireless sensor networks, which somehow tried to increase networks lifetimes. In this study, we dealt with this problem using a more efficient method by taking parameters such as the distance between two sensors into account. In this paper going to see about various types of automata based algorithm namely, Learning Automata Based Coral Reefs Optimization Algorithm, Stochastic Minimum Spanning Tree Algorithm**,** S-Laid: Simple La-Based Intrusion Detection and their learning automata models.

Keywords- Learning Automata, S-Laid, Optimization, Minimum Spanning Tree.

1. Introduction

Wireless sensor networks consist of a large number of inexpensive sensor nodes distributed densely in the environment, having limited energy and on the other hand, consuming a great deal of energy in order to send information to central node directly. Thus, in most cases, nodes communicate with central node via their neighbors. On one hand, there are different paths to central node from each node, so optimal path must be selected. The frequent use of one path results in energy reduction of sensors located on that path, ultimately resulting in sensor loss. Therefore, we tried to increase networks lifetime by providing an intelligent algorithm and taking such parameters as sensor lifetime, remaining and consumption energies of sensors and distances between sensors into account, in order to have an almost optimal data aggregation in networks. The attractiveness of our LA-based approach is that it uses the S-model, in which the input to the automaton from the environment can be completely favorable, completely unfavorable, or some continuous intermediate value depicting partially favorable or partially unfavorable situations. Most of the varieties of existing LA-based solutions for different problems that exist in the literature use the P-model approach, in which the feedback from the environment to the automaton is either favorable or unfavorable.

The S-model approach that we took helps us to model the environmental feedback for partially favorable/unfavorable cases as a ratio of the number of malicious packets found and the number of packets that are sampled by the IDS.

The basic differences between LAID and S-LAID are catalogued below:

(1) LAID is a centralized protocol, where as S-LAID is a distributed protocol. (2) Unlike in the case of LAID, S-LAID functions without the knowledge of adjacent nodes or the network's topology. (3) The learning functions in S-LAID are simpler to execute. (4) In LAID, we considered the system budget as a whole. It was considered as the number of packets the system (network) can sample in a given time period. In S-LAID, the system budget is fixed for the lifetime of a node. It is the total number of packets that one node can sample during its lifetime. (5) Memory requirements for LAID are more than those for S-LAID. S-LAID requires very little memory to function.

The purpose of CRO initialization is to set parameters to fill in the algorithm. The main control parameters of CRO are presented as follows: coral reef, Λ, consisting of a $T \times M$ grid similar to the population size in the evolutionary algorithm (EA), the girds are selected randomly and can assign a coral or colony of coral, representing a solution to the given problem, the rate ρ_0 between the selected grids and not selected ones which is an important factor to control the exploration ability of the algorithm. The health function f is similar to the fitness of EA. The underlying idea behind CRO is that as the reef progresses, the more healthy the corals are (which represents a better solution to the mentioned problem), the better the chance they can survive. A novel method for addressing the problem of dynamic point coverage in wireless sensor networks using learning automata. Each node is equipped with a learning automaton which learns (schedules) the proper on and off times of that node based on the movement nature of the target points. This solution is a dynamic scheduling solution to this problem which not only has the advantages of scheduling methods, but also addresses the two shortcomings of these methods mentioned earlier. This is because in this method, each node (or better the automaton of each node) learns its best on and off schedules using only the information of the moving targets passing through its sensing area, and hence no notification messages exchanged between on and off nodes.

An intelligent algorithm based on distributed learning automata to aggregate data in wireless sensor networks. Each host is equipped with a learning automaton; sink node is considered as root, and then given the action probability vectors, learning automata select next action randomly from variable actions set of learning automata. This process continues until the entire network is covered and minimum spanning trees are formed. Then, the message of data aggregation is sent to all nodes from sink node in minimum spanning tree.

2. LITERATURE SURVEY

- **Habib Mostafaei, Antonio Montieri, Valerio Persico, Antonio Pescapé** proposed PCLA, a novel algorithm that relies on Learning Automata to implement sleep scheduling approaches. It aims at minimizing the number of sensors to activate for covering a desired portion of the region of interest preserving the connectivity among sensors. Simulation results show how PCLA can select sensors in an efficient way to satisfy the imposed constraints, thus guaranteeing good performance in terms of time complexity, working-node ratio, scalability, and WSN lifetime. Moreover, compared to the state of the art, PCLA is able to guarantee better performance. **Sudhanshu Tyagi, Neeraj Kumar** proposed most popular protocol for clustering in WSNs is Low Energy Adaptive Clustering Hierarchy (LEACH) which is based on adaptive clustering technique. This paper provides the taxonomy of various clustering and routing techniques in WSNs based upon metrics such as power management, energy management, network lifetime, optimal cluster head selection, multihop data transmission etc. **Lizhi Cao, Ying Chen** proposed on ICLA protocol adopting the learning automata (LA), an energy balanced unequal clustering algorithm with considering the node density. The approach considers the residual energy and the node density in cluster head election and adopts LA for information exchange with the surrounding environment, so it can choose relatively better cluster heads. Meanwhile, according to the distance between cluster heads and the base station and node density, a series of unequal clusters are formed to balance the energy load of intra- and inter-clusters in different positions and node density degrees of networks. The approach also adopts an evaluation function to choose optimal relay cluster heads and form multihop routing, which achieves a tradeoff between the energy of cluster heads, node density in cluster and distances from cluster heads to the base station. Therefore, it can achieve the goal of optimizing cluster heads selection and balancing energy load among all sensor nodes in the network. **Manju,Satish Chand, Bijender Kumar** propose an energy-efficient scheduling algorithm based on learning automata for target coverage problem. The learning automata-based technique helps a sensor node to select its appropriate state (either active or sleep). To prove the effectiveness of their proposed scheduling method, they conduct a detailed set of simulations and compare the performance of their algorithm with the existing algorithms. **Sudeep Tanwar, Sudhanshu Tyagi, Neeraj Kumar, Mohammad S. Obaidat** propose a learning automata-based multilevel heterogeneous routing (LA-MHR) scheme for WSNs. In an LA-MHR, S-model-based LA is used for cluster heads (CHs) selection. A base station (BS) is used to allocate the cognitive radio spectrum to selected CHs. Moreover, single-hop communication among different SNs is used as multihop communication. It suffers from energy holes problem in WSNs. Based upon the initial energy of SNs, these are divided into intermediate, advanced, super-intermediate, and super-advanced categories. The performance of LA-MHR is evaluated by varying the locations of BS and heterogeneity parameters of SNs. Extensive simulations are performed to evaluate the performance of LA-MHR. Performance evaluation results show that both the network lifetime and stability of LA-MHR are increased by more than 10% as compared to other competing preexisting protocols such as EHE-LEACH, E-SEP, LA-EEHSC, and MCR. **Habib Mostafaei and Mohammad S. Obaidat** propose an irregular cellular learning automaton (ICLA)-based algorithm, which is called SPLA, to preserve sensors protection. Learning automaton at each cell of ICLA with proper rules aims at investigating the minimum possible number of nodes in order to guarantee the self-protection requirements of the network. To evaluate the performance of SPLA, several simulation experiments were carried out and the obtained results show that SPLA performs on average of 50% better than maximum independent set and minimum connected dominating set algorithms in terms of active node ratio and can provide two times reduction in energy consumption. **M. Gholipour and M. R. Meybodi** proposed learning automata based mobicast protocol for sensor networks to support applications which require spatiotemporal coordination. The proposed protocol which we call it LA-Mobicast uses the shape and the size of the forwarding zone to achieve high predicted accuracy. The proposed protocol use learning automata to adaptively determine the location and the shape of the forwarding zone in such away that the same number of wake-up sensor nodes be maintained. The proposed protocol is a fully distributed algorithm which requires lesser communication overhead in determining the forwarding zone and the mobicast message forwarding overhead. In order to show the performance of the proposed protocol, computer simulations have been conducted and the results obtained are compared with the results obtained for five existing mobicast protocols. The results of comparison show that the proposed protocol outperforms existing mobicast protocols in terms of slack time, message exchange, node involved and guarantee percent. M. Asemani, M. Esnaashari proposed a novel data aggregation algorithm, called LAG, which tries to mix all of these criteria for finding the routes. Furthermore, by considering the fact that the remaining energy of a sensor node and its possibility for aggregating data received from other nodes may change during the operation of the network, the proposed LAG algorithm tries to dynamically adapt itself with such changes and to select new routes towards the sink accordingly. The adaptive behavior of LAG is the result of using learning automata (LA). Each node is equipped with an LA which helps the node selects its next hop for forwarding data towards the sink considering all of the three mentioned criteria. The learning automaton used in LAG algorithm, called INCASE-LA, is introduced in this paper for the first time.

3. AUTOMATA BASED ALGORITHM

3.1 Learning Automata Based Coral Reefs Optimization Algorithm

The learning automata based coral reefs optimization algorithm (LACRO for short), performs like the original CRO algorithm with the auxiliary section at the end of the each iteration to select CRO parameters value. In order to enhance the ability of the original CRO algorithm, we borrow the idea from the differential evolution and the genetic algorithm to make some modifications to the basic process of the CRO algorithm. The great difference between the original CRO algorithm and the proposed method lies in that the mutation of the selected brooding coral is controlled by the parameter B_d, which is adaptive and adjusted by learning automata according by the diversity and evolutionary status of the population. In contrast to the proposed algorithm, the fraction of corals that reproduce by brooding is 1-F_b in the original CRO. In addition to the parameter of the brooding radio controlled by the learning automata, the parameter of Broadcast Spawning radio F_b is also adaptive and adjusted by the learning automata. The details of the proposed algorithm are presented as follows:

Step 1: Coral reefs initialization. Set the initial parameter values for the coral reef population, the learning automata and determine the way of encoding the solution. Considering the characteristics of the solved problem, we use the binary code method.

Step 2: Equally discretize two parameters, namely, the value of F_b and B_d, into the m_1 distant value and m_2 distant value, respectively. This method is called the adventurous method which allows a parameter to change radically from one end of its range to the other in the consecutive iterations and not to be restricted by its previous value.

Step 3: To equip each parameter with one learning automaton LA_i ($i = F_b, B_d$), in which the corresponding actions number is m_1 and m_2, respectively. During every iteration, LA_i ($i = F_b, B_d$) chooses one from its action set, then the corresponding value of the selected action will be set as the new value for the parameter. All the coral reefs have the same values for the parameter F_b and B_d. In each iteration the roulette-wheel selection method is used to select the corresponding action of each learning automaton.

3.2 Stochastic Minimum Spanning Tree Algorithm

A heuristic algorithm called LA-SMSTA to find an optimal solution from SMST problems where edges' weights are unknown. When the weights of edges change with time, finding optimal solution from MST problem becomes too difficult. Suppose that G(V,E,W) represents entries of stochastic graph, where $V=\{V_1,\ldots,V_2\}$ is nodes set, $E = \{e_1, e_2,\ldots,e_m\} \subseteq V\times V$ is edges set, and matrix W represents the weights assigned to edges set. In this algorithm, a network of distributed learning automata is formed by equipping each node of the graph with a learning automaton. Edge $e_{(i,j)}$ relates either to action j α_i of learning automata Ai or to action j α_i of learning automata A_j. This means that each of learning automata can select each of edges as an action. Selecting action j α_i by automata Ai adds edge $e_{(i,j)}$ to MST. Weight $W_{i,j}$ is the weight assigned to edge $e_{(i,j)}$ and assumed to be a positive stochastic variable. For the proposed algorithm, all learning automata are in a passive state in the primary set. The proposed algorithm includes some steps at each of which one of possible spanning trees is identified randomly. The algorithm is based on distributed learning automata, which surveys them by means of backtracking technique in order to discover spanning trees. Any steps of LA-SMSTA algorithm begins randomly with selecting one of graph's nodes as a sink node. Learning automata related to chosen node are activated and one action is selected based on actions probability vector. The edge related to this selection is added to spanning tree already made. The weight assigned to the chosen edge is added to total weight of spanning tree. To avoid forming a loop in a tree, each of active learning automata trims its own actions set. Then, the learning automata located at other end of chosen edge is activated, which also selects one of its own actions and activates the automata located at its end. The process of sequential activation is repeated from learning automata (or from selection of tree edges) until it leads to two following states: in the first state, spanning trees are formed, and in the second, current active learning automata has no action to choose. In the former, the current step is completed successfully by finding a solution for the problem of spanning trees with minimum weights (this happens when the number of selected edges $\geq$ n-1, where n shows cardinality of nodes set), and in the latter, learning automata are found through backtracking process, are activated again, and actions set of automata is updated by disabling the last chosen action. Afterward, the activated automata resume the current step by selecting one of possible actions. The process of activating learning automata continues until spanning trees are formed. Then, data aggregation is performed within middle nodes and the results are sent to central node in the form of a single packet. By means of backtracking technique, each of learning automata may activate more than one of its neighbors at each step. In other words, any learning automata can select more than one action. As stated earlier, respective edge is added to spanning tree, and this task is chosen by learning automata. Also, the weight assigned to selected edge is added to total weight of spanning tree.

3.3 S-Laid: Simple La-Based Intrusion Detection

Intrusions can result in denial of service (DoS) attacks, virus activities, spoofed, altered or replayed routing information, sinkhole attacks, wormhole attacks, Sybil attacks, HELLO flood attacks, and so on. Irrespective of the type of attack, the primary intent of the intruder is to gain access to network resources, typically, by sending malicious packets to a specific node(s) in the network.

3.3.1 Learning automata model

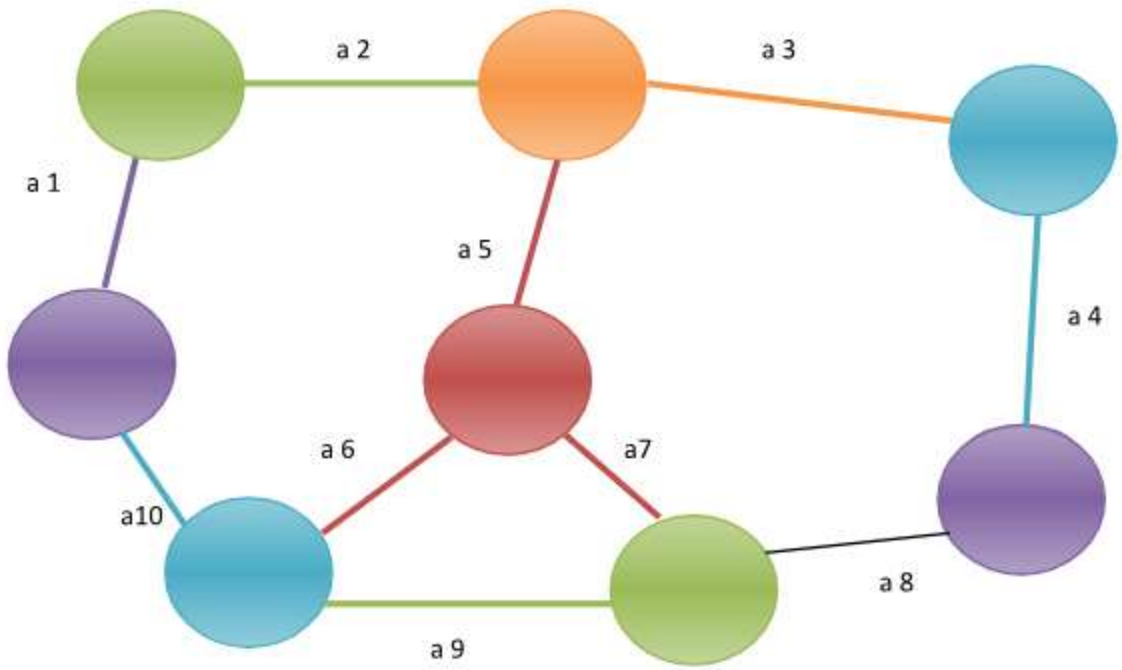

Figure 1 - A WSN with a set of paths

We present our LA-based model for intrusion detection in WSN. Let us define the following parameters:

1. α: { $\alpha_1,\alpha_2....\alpha_r$}, be the set of sampling rates that in the system.
2. β: Environment response set for an action $\alpha_{i..}$
3. n: A time instant.
4. Z: Reward Constant (0≤Z≤10): The reward constant is a learning parameter used to update the sampling rate.

Initially, for the paths {α_1, α_2 .... α_r} , the action probabilities {$p_1(n)$, $p_2(n)$, ..., $p_r(n)$} and their corresponding exposures {$Y_1,Y_2 ....Y_r$} are assigned the same value to ensure fairness. In other words:

$$a_{1 \text{ to } r} = Y_{1 \text{ to } r} = \frac{1}{r}$$

Also, we consider the following parameters:

1. S: The sampling budget of the system.
2. Sample Table: This is a table which holds information about (path, β) for all paths that are under an attack.
3. X: Constant associated with the sampling process (0<X<1).
4. Q: The attacker’s budget.

CONCLUSION

In this paper analysed algorithms for enhance the learning automata based. A learning automata-based algorithm which equips the ability to create spur-in-time responses with better exploration/exploitation capabilities. The parameters of F_b and B_d are discretized within their permitted ranges, and a learning automaton with a finite action set is used for each parameter. The combined effort of all the nodes in the network will help in removing most of the malicious information from the network. The nodes are self-learning in nature and the LA is used to optimize the packet sampling efficiency in the nodes. Perform a 'neck-to-neck' comparison of LAID with different other IDS developed for WSN. Each one method or algorithm have some performance ratio not only the advantages and also have some drawbacks within that. In future work will choose any one algorithm which is most secure and suitable to do better accuracy for automata based process and then apply some enhancement within that to proof much better than the old performance.

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