

## Localization Protocol Based on Learning Automata for Wireless Sensor Networks

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**Abstract.** Location discovery in sensor networks is considered to be a vital sine qua non for supporting various applications. Thus, sensors are to be infused with their location in the network, via the localization process. The process could be carried out during the establishment of the network, and while the location of sensors are varied as well. In the following research, a protocol based on learning automata, using two anchor sensors for the localization in sensor networks has been proposed. Simulation results demonstrate that the proposed method yields lower cost standard, and lower error in the location approximation of nodes, in comparison with AOA and PSO algorithms.

**Keyword:** wireless sensor network, Learning automata, Localization, anchor sensor

### 1. Introduction

Sensor network are comprised of numerous (which may reach thousands of) minute sensors, which are of low cost, high capability, and low energy storage. These sensors can obtain information from the surroundings, and send it to juxtaposition sensors [1]. Sensor networks could be applied in the intelligent surveillance of highways, relief operation in accidental incidents, monitoring the perimeter, target tracing, and recording valuable data such as sonic, visual, and thermal observations; and also in seismology [2].

Localization problem is so general an issue. In some applications, particularly indoor localization, for instance "in bedrooms" we only need to recognize the environment that the sensor is sited. But in most of the applications, the physical location for the sensor is required. The physical location could be absolute (such as longitude and latitude), or could be in a supposed coordinate system as relative. We need to note that various parameters are liable to assist in the localization of sensors, and every sensor in a sensor network is able to sense the surrounding information. Other sensors existing in the network use information such as the distance to the sensors-which is measurable through different methods-or angle of arrival from the sensors, to figure their location. Some other localizing methods in sensor networks, are not depending on the distance or angle measuring and other parameters, and solely localize sensors, by investigating their connection or disconnection. Some scarce methods have been suggested too, which do not use anchor sensors.

The rest of the research sections are organized as follows: anterior works are presented in section 2, and as it proceeds, we discuss AOA algorithms in section 3, and learning automata in section 4, the proposed protocol and experiment results are respectively exhibited in sections 5 and 6, and with conclusion in section 7, it is brought to a close.

### 2. Studying anterior works

Various localizing methods are set forth in this section. In these methods, it is supposed that networks are static, and their topology remains consistent during the time. As all the distributed algorithms are operated locally, topological changes of the network brings about a resumption of localization for all the groups whose locations have been affected.

Approximation point-in-triangulation method is arrange-free method [3] which requires a heterogeneous network, in which minority of sensor nodes are equipped with powerful transmitters which are able to obtain positional information through GPS or other mechanisms. The method using beacons transmitted by anchors, applies an area-based method to procure an approximate position through the division of the environment into triangular areas.

N-hop Multimodal method suggested in [4] is a granular and absolute positioning method, performed in three phases. The first phase accounts for the distance approximation of each node to some anchors, the second one estimates the position of each node, using the previous phase information, and the third one deals with the refinement of node estimated position, through the least squares estimation.

Positioning is an optimization issue, without restriction [5]. In recent years, there have been proposed various positioning algorithms, which have been based on optimization. Micro genetic algorithm has been offered for the improvement of APS method [6]. A modified method of iterative Multimodal has been proposed based on particle swarm optimization (PSO), which is of high precision. Simulated annealing has been utilized as an optimizing means. And concentrated positioning method again based on PSO has been offered, which corresponds with simulated annealing, but is more precise than the former [7].

### **Angle-Of-Arrival (AOA)**

Is an algorithm which operates depending on the arrival angle of data, and the data is regularly obtained through a radio antenna, or a microphone, and permit a listening sensor node to distinguish the transmitter node direction. In these methods, generally several distinct microphones listen to a transmitted mono-signal, and estimate the angle of arrival and the distance, by analyzing the phase difference and the time difference among the arrival signals at different microphones [8].

### **Learning Automata**

Learning automata [9] are elements designed to be incorporated in a plausible and indefinite environment. This machine performs some finite operations. Each learning automata has a vector of probabilities and the vector illustrates the probability with which an operation is done and the total sum of the entries equal one.

By doing an operation through an automata, a selected action is analyzed via a plausible environment, and the analysis result is transferred to the automata as a positive or negative signal, and the automata is influenced by this response, in the options ahead. The aim is for the automata to choose the best action among its options. The best action is seemingly the one that maximizes the probability of receiving a reward from the environment. The functionality of learning automata is in interaction with the environment.

### **Proposed Protocol**

The localization protocol proposed in this research has been designed with prospects for a decline in cost and an increase in speed, with the application of learning automata. The problem definition for the proposed protocol is as though a network comprising of  $N$  sensors is presumed, in which  $M$  sensors of total  $N$  sensors have unknown locations, and the objective is to discover the position of  $M$  sensors, using the anchor sensors whose number equal  $N - M$ . The function of sufficiency is assumed based the squares sum between the target sensor and the anchor sensor, and is defined as equation 3.

In which  $(x, y)$  stands for the coordinates of the target sensor, and needs to be specified; and  $(x_i, y_i)$  stands for the coordinates of the anchor sensor number  $i$ .  $d_i$  represents the measured distance between the target sensor and anchor sensor number  $i$ , which is arriving from localization phase, using AOA protocol, and is liable to errors.  $N_a$  accounts for the number of the anchor sensors, whose positional information is received by the target sensor. In the proposed protocol, the prominence is given to the application of two anchor sensors for target node location approximation. This research, using two anchor sensors as opposed to anchor-based methods which emphasize on three anchor sensors, endeavors to meet its objective with a lower cost and a higher speed, using

two anchor sensors. the distance and the angle between the target sensor and anchor sensor are calculated in the first phase, which are carried out via AOA.

The covered area in figure 1 is displayed with blue color, which includes the target sensor. To estimate the exact position of the sensor, we need to primarily approximate sensor location as follows:

$$f(x, y) = \sum_{i=1}^{Na} (d_i - \sqrt{(x-x_i)^2 + (y-y_i)^2})^2 \quad (1)$$

$$(x_2, y_2) = (x_1 + d \cos \alpha, y_1 + d \sin \alpha) \quad (2)$$

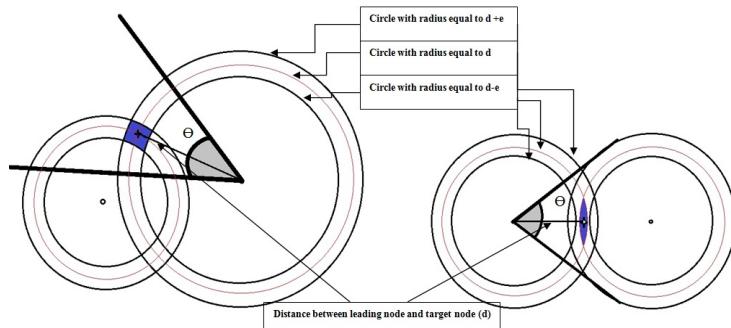


Fig. 1. Various conditions of two the anchor sensor covering on a sensor node

In which  $y_i$  and  $x_i$  represent anchor sensor coordinates, and  $y_2$  and  $x_2$  stand for anchor sensor preliminary estimated coordinates. Also,  $\alpha$  is the angle and  $d$  is the estimated distance achieved in the first phase.

As the so-called protocol is based on two anchor sensors, so two preliminary estimated points are yielded respectively, using the coordinates of each anchor sensor, which we apply equation 3 to achieve the best preliminary estimated point for the target sensor.

$$(x, y) = \left( \frac{1}{2} \sum_{i=1}^2 x_i, \frac{1}{2} \sum_{i=1}^2 y_i \right) \quad (3)$$

$$\epsilon = \sqrt{\frac{s}{n}} * \left( 1 - \frac{\text{iteration}_{\text{cur}}}{\text{iteration}_{\text{max}}} \right) \quad (4)$$

As the preliminary point not being a precise approximation, a learning automata is allocated to it, which conducts it to the final answer. The learning automata consists of a limited number of actions which have been predefined for it. In point of fact, these actions account for preliminary point movement towards new locations. Eight directions are presumable for the movements. Therefore, the automata is composed of eight actions  $\alpha = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7, \alpha_8\}$ , which each of them primarily are equally on a probability of 0.125.

Action 1 :  $(x_{\text{new}}, y_{\text{new}}) = (x + \epsilon, y + \epsilon)$  , Action 2 :  $(x_{\text{new}}, y_{\text{new}}) = (x + \epsilon, y - \epsilon)$  , Action 3 :  $(x_{\text{new}}, y_{\text{new}}) = (x - \epsilon, y + \epsilon)$

Action 4 :  $(x_{\text{new}}, y_{\text{new}}) = (x - \epsilon, y - \epsilon)$  , Action 5 :  $(x_{\text{new}}, y_{\text{new}}) = (x + \epsilon, y)$  , Action 6 :  $(x_{\text{new}}, y_{\text{new}}) = (x, y - \epsilon)$

Action 7 :  $(x_{\text{new}}, y_{\text{new}}) = (x, y + \epsilon)$  , Action 8 :  $(x_{\text{new}}, y_{\text{new}}) = (x - \epsilon, y)$

Parameter  $\epsilon$  stands for the movement quantity from current coordinates. The parameter is assigned so that it declines with respect to the algorithm progression and iteration increase in order for the plausible movement space to contract, as it closes in to the target point with equation 4.

Which  $S$  stands for square area space that the sensors are incorporated in and  $N$  represents the number of sensors. As a matter of fact,  $\sqrt{\frac{s}{n}}$  is the desired distance between the nodes.  $\text{Iteration}_{\text{cur}}$  is the number of current iteration, and  $\text{Iteration}_{\text{max}}$  is the maximum number of iteration, and is calculated experimentally. In the first step, the assessment function quantity for the estimated point coordinates from the preliminary estimation is primarily achieved. Then, the learning automata stochastically selects an action, based on its action probability vector, and the assessment function is calculated for the recent location that the action distinguishes. If assessment function quantity was lower than previous, the transfer would be carried out to a new position. The decline in assessment function quantity means receiving the desired response from the environment, which the selected

action is rewarded via equation 5; the probability of  $\alpha_i$  increases, and the probability of other actions diminishes, which is penalized via equation 6. Action probability changes are as follows:

$$P_i(n+1) = p_i(n) + a[1 - p_i(n)] \quad (5) \quad P_j(n+1) = (1-a)p_j(n) \quad \forall j, j \neq i \quad (6) \quad \text{Where } 0 < a < 1$$

On the contrary, if the received response from the environment is undesired, the probability of  $\alpha_i$  based on equation 7 declines, and the probability of automata's other actions increases. Anyhow, the changes are yielded in a way that the overall  $P_i(n)$  sum constantly equals 1. Action probability changes are as follows:

$$P_i(n+1) = (1-b)p_i(n) \quad (7) \quad p_j(n+1) = \frac{b}{r-1}(1-b)p_j(n) \quad \forall j, j \neq i \quad (8) \quad \text{Where } 0 < b < 1$$

$r$  stands for the action number of automata,  $a$  for reward parameter, and  $b$  for penalty parameter.

The algorithm opts for the more probable actions in subsequent iterations, and figures the quantity of the target function. The rest of the stages proceed as before. The algorithm is terminated once maximum iteration is achieved, or parameter  $f$  equals zero.

### Proposed method functionality assessment

In the following section the assessment of the proposed method is discussed. The proposed method has been analogized to two positioning methods as AOA standard positioning, and PSO-based algorithm positioning. NS-2 software has been applied in the simulation of network environment. Along all the experiments, the sensors have been put into a  $100 \times 100$  environment. The proportion of anchor sensors took up 10 percent of the overall sensors. the number of sensors is in order 30, 50, 70, 100, 150, and 200, the radio ranges in order 15, 20, 24, and 30, the number of anchor nodes 10%, 15%, 20%, 19%, and 30% of the overall sensors, AOA error parameter 10%, reward parameter ( $a$ ) 0.75, and penalty parameter ( $b$ ) is assumed 0.25. For the implementation of PSO method, the numbers of particles and maximum iterations have been respectively presumed as 20 and 30, which are presented in the simulation results of figure 2.

Diagram (a) illustrates the error in positioning for different network nodes, when the total amount of anchor sensors equals 10%, which the positioning error in the proposed method tends to be lower than the two other methods. Diagram (b) points out the effect of radio range on the positioning error, which the neighbors of each sensor increase with the expansion in sensors radio range. Consequently, the probability of finding appropriate anchor sensors grows. Diagram (c) indicates the influence of the number of anchor sensors on the positioning error, which in such a condition the number of sensor nodes is presumed as consistent and equal to 150, and with the rise of anchor sensors, the positioning error declines. Furthermore, diagram (d) exhibits the average positioning error in lieu of various quantities of learning automata parameters.

As evident in the following figure, the simulation results imply the superiority of the proposed protocol over other positioning methods.

### 3. Conclusion

In this study, a localization protocol based on learning automata for wireless sensor networks called *WSNLA* has been suggested, which plays a fundamental role in diminishing the number of anchor sensors, and also in cases where an adequate amount of anchor sensors is not available. In the proposed protocol, it is possible to estimate the location of a target sensor with high precision and speed, using two anchor sensors. But in the previous methods which were anchor-based, at least three anchor nodes were prerequisite for the exact location discovery of a target sensor. Protocol *WSNLA* is simulated in NS-2 simulator, and is analogized to PSO-based protocol-which uses intelligent methods for the localization-and AOA standard protocol.

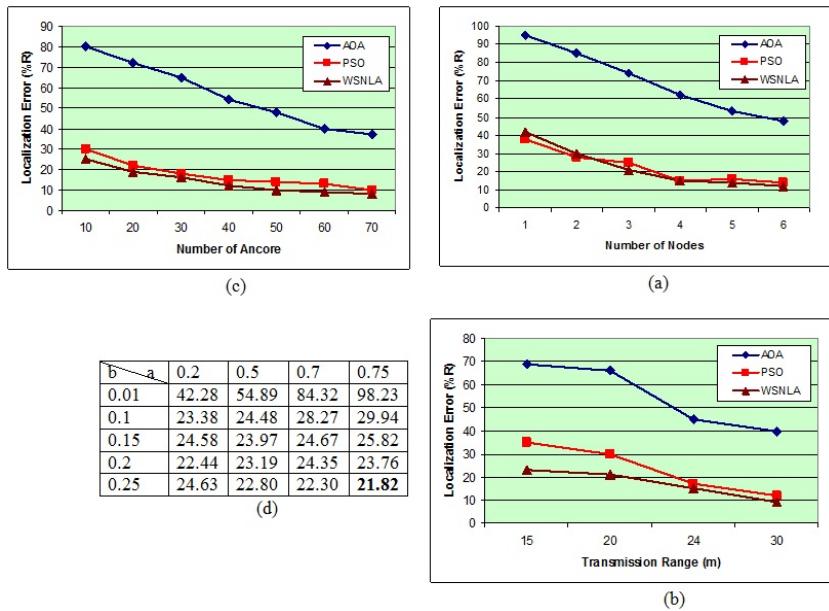


Fig. 2, Simulation results of WSLNA proposed protocol using PSO and standard AOA methods

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