Node Localization in Wireless Sensor Networks by Water Cycle Algorithm

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Abstract: Wireless sensor networks have numerous practical uses which make them interesting and active research topic. Beside the information collected by wireless sensor networks, usually location of the sensor is necessary in order to have complete and useful information. Since it is rather expensive to put GPS receivers in all sensors, different localization techniques were developed. Usually a small number of nodes are equipped by GPS receiver while the location of the rest nodes is determined based on the received signal strength. Finding the positions of sensors is a hard optimization problem and in this paper we propose recent swarm intelligence optimization algorithm - water cycle algorithm. The proposed method was compared to other methods from literature and it was proved to be better considering all quality indicators.

Key–Words: water cycle algorithm, global optimization, swarm intelligence, metaheuristics, wireless sensor networks, localization

1 Introduction

Wireless sensor networks (WSN) consist large number of sensor nodes deployed in the area of interest. All sensors work together in order to achieve the common objective. Sensor nodes are low-cost and low-power, samll in size and have limited resources, communication capability and storage [1]. Each sensor node in the wireless sensor networks collects data such as sensing vibration, temperature, motion or detect different pressure in the monitoring area. WSN have found purpose in numerous applications [2], [3], [4], [5].

When location of the sensor nodes are unknown, information collected from them is usually unmeaning and useless. In order to determine sensor nodes positions, numerous localization techniques were proposed. The easies and well-known technologies for localization is the global positioning system (GPS). By putting GPS receivers in each sensor node, locations can be determined, but it is too expensive. Better solution is to post the GPS only on limited number of nodes named anchor nodes. Anchor nodes locations are known while the sensor nodes locations have to be determined. Sensor node estimate the distance from all anchor nodes location by using ranging techniques, and then compute its location.

Numerous studies deal with the problem of localization of nodes in the WSN. Finding the positions based on the all estimated positions from the inaccurate distance information represents hard optimization problem. For solving these problems stochastic population based metaheuristics have been used successfully. Some of the well known and widely used methaheuristics are swarm intelligence algorithms. For example, bat algorithm [6] was applied to support vector machine optimization [7], handwritten digit recognition [8], RFID network planning [9], fireworks algorithm [10] was used for image processing problems [11], [12], [13], optimizing machine learning algorithms [14], brain storm optimization algorithm [15] was applied to path planning problem [16], drone placement [17], elephant herding optimization [18] was used for solving coverage problem [19], [20], support vectore machine parameter tuning [21], [22], multilevel image thresholding [23], etc.

Swarm intelligence algorithms were also applied to numerous wireless sensor network problems such as node localization [24], [25], [26], [27] and coverage problem [28], [29].

In this paper we propose recent water cycle algorithm [30] for solving localization problem in WSN. The rest of the paper is organized as follows. Mathematical model used for node localization was described in Section 2. Water cycle algorithm applied to sensors localization was presented in Section 3. Experimental results and the conclusion were given in Section4 and Section 5, respectively.

2 Mathematical Model for Localization of Unknown Nodes in WSN

Mathematical model used in this paper was presented in [31]. The sensor network is represented in three-dimensional coordinate system while sensor nodes are coordinate points. Nodes in the WSN are fixed and the position of the anchor nodes is known. The unknown node based on the received signal strength index (RSSI) between them and anchor nodes, determines its position.

If the sensor node is in the range of anchor node as well as the anchor node is in the range of radio signals transmitted by the sensor node, localization will be possible. The sensor with unknown position will measures the power of the received radio signal coming from at least three anchor nodes and that power will be used for estimating the distance between corresponding nodes.

The aim of this paper is to estimate coordinates of the unknown nodes as close as possible to their real locations. In order to define the problem, the following notation will be used. N is the number of sensor nodes posted in the three-dimensional space while M is the number of anchor nodes equipped with GPS tags. For two nodes i and j the distance obtained by RSSI ranging techniques is $d_{i,j}$. Received radio signal is converted in dBm and it is calculated by the following equation:

$$P_r\left(d\right) = \frac{P_t G_t G_r \lambda^2}{4\,\pi^2 d^2 L} \tag{1}$$

where P_r is the received power of wireless signal, P_t is the transmitted power of wireless signal from the anchor node, G_t is the antenna gain of the anchor, G_r is the antenna gain of the sensor node, L is the system loss, λ is the system wavelength and d is the distance between the sending and receiving nodes. In most cases $G_t,\ G_r$ and L are equal to 1 [32], [33].

The distance can be determined by the following equation:

$$d = \sqrt{\frac{P_t G_t G_r \lambda^2}{4\,\pi^2 P_r L}} \tag{2}$$

This distance (Eq. (2)) represents the estimated distance which means that it has some measuring error. The real distance between the two nodes i and j can be obtained by:

$$r_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2} \tag{3}$$

Localization problem in WSN can be considered as an optimization problem where the goal is to minimize the difference between estimated and the real distances. If (x, y, z) is the real location of an unknown node T_i, (x_j, y_j, z_j) the coordinate of A_j anchor node, and d_{ij} is the measured distance between T_i and A_j where $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, M$, then an optimization problem whose purpose is to find the optimal solution for (x, y, z) is defined by the following equation:

$$f\left(x, y, z\right) = \sum_{i=1}^{N}\sum_{j=1}^{M} \left|r_{ij} - d_{ij}\right|. \tag{4}$$

or

$$f\left(x, y, z\right) = \sum_{i=1}^{N}\sum_{j=1}^{M} \left(r_{ij}^2 - d_{ij}^2\right)^2. \tag{5}$$

The goal is to minimize the fitness function. In the next section we describe the recent water cycle algorithm used for minimizing the fitness function defined in Eq. 5.

3 Water Cycle Algorithm for Node Localization

Water cycle algorithm (WCA) is swarm intelligence optimization algorithm proposed by Eskandar et al. in 2012 [30]. Originally, it was tested on constrained engineering problems while after in [34], WCA was applied to both, unconstrained and constrained optimization problems. In [35], modified WSA algorithm was proposed for solving multi-objective optimization problems and in [36] it was also adjusted for constrained multi-objective problems. It was applied to numerous problems such as controlling reservoir systems[38], weight optimization of truss structures

[39], interactive operation management of a micro-grid [40], etc. Bare bones WCA was proposed for optimal reactive power dispatch in electrical power systems in [41].

Water cycle algorithm is based on the natural phenomena of the water cycling. The complexity of this phenomena was reduced and summarized into several steps that represent steps and operations of the swarm intelligence algorithm. Detail description of the phenomena can be found in [30]. In general, it can be described as follows. Streams flow to the rivers while the rivers flow downhill toward the seas and the water from the all three, sea, rivers and streams, evaporated after which clouds are generated. Clouds carry the water until releases it in the form of rain.

Definition of the water cycle algorithm is as follows. The initial population of size N are raindrops and they represent random solutions in the search space with lower limit LB and upper limit UB:

$$x = LB + (UB - LB)rand \tag{6}$$

where $rand$ is an uniformly distributed random value in range $[0, 1]$. The first algorithm's parameter is N_{sr} and it represents the number of rivers along with the one sea. The best solution is saved as a sea, denoted by X_{sea}. The next $N_{sr} - 1$ best solutions are rivers and all other solutions ($N_{raindrops} = N - N_{sr}$) are the raindrops that flow toward the rivers and sea. Each of the N_{sr} best solutions have some number of worse solutions that moves toward them (that are the raindrops that form stream and flow to the specific rivers and sea). The number of solutions that will flow toward the better solutions is determined by the following equation:

$$NS_n = \text{round}\left\{ \left| \frac{Cost_n}{\sum_{i=1}^{N_{sr}} Cost_i} \right| N_{raindrops} \right\}, \tag{7}$$

where NS_n is the number of solutions that will move toward the solution X_n where $n = 1, 2, \ldots, N_{sr}$, and $Cost_i$ is the value of fitness function for the solution X_i.

The new solutions are generated in each generation as follows:

$$X^{i+1}_{stram} = X^i_{stream} + C(X^i_{river} - X^i_{stream})rand \tag{8}$$

$$X^{i+1}_{river} = X^i_{river} + C(X^i_{sea} - X^i_{river})rand \tag{9}$$

where $rand$ is random number in range $[0, 1]$ drawn from uniform distribution. Parameter $1 \leq C \leq 2$ is algorithm's parameter that enables movement in different directions toward the corresponding solutions.

By applying described operations, exploitation was implemented. On the other hand, exploration was introduced as evaporation process. In WCA, it was implemented in the following way. If there is a solution closer to the best one more than threshold value d_{max} then that solution is replaced by the random obtained by Eq. 6.

WCA parameter d_{max} is used to control the exploration. If it has larger value, then the solutions will be replaced approaching close to the best one. In practice it means that the space around the best solution will not be extensively explored. This is not a desirable behavior in the final stages of the optimization algorithm but it is highly necessary at the beginning so the algorithm would not be trapped in local optima. Based on these parameter d_{max} should be larger at the beginning and reduced in later stages of the WCA. It was accomplished by controlling parameter by the current iteration number [30]:

$$d^{i+1}_{max} = d^i_{max} - \frac{d^i_{max}}{maxIter}, \tag{10}$$

where $maxIter$ represents the maximal number of algorithm's iterations.

In this paper, WCA was used for finding the optimal solution based on the fitness function defined in Eq. 5.

4 Simulation Results

The proposed WCA method was implemented in Matlab 2016b. All experiments were conducted at the computer with Intel ® Core™ i7-3770K CPU at 4GHz, 8GB RAM, Windows 10 Professional OS.

Experiments were organized same as in [42] since the results obtained by our proposed method were compared with the particle swarm optimization algorithm described in that paper [42]. The sensing range of anchor nodes was 87 m, while the range of sensor nodes was 30 m. Wireless sensor network contains 20 sensor nodes randomly deployed in the monitoring area of 50m×50m×50m, and for 4 anchor nodes (not coplanar). The locations of the anchors were set as follows: $A1$ (50,0,0), $A2$ (0,50,50), $A3$ (50,50,50) and $A4$ (0,0,50).

Parameters of the WCA were set in the following way. Population size was N =100, while N_{sr}, the

Table 1: Localization error comparisons under different ranging errors

Rang	**WCA**			**TLP**		
err. %	Avg	Min	Max	Avg	Min	Max
0	0.000	0.000	0.000	0.212	0.011	0.463
5	1.454	0.998	1.942	4.980	1.290	9.670
10	2.871	2.402	3.338	9.660	3.980	17.259
20	5.575	4.413	6.965	19.670	6.120	26.592
30	8.196	6.207	9.567	27.921	14.780	39.257
40	10.658	7.702	11.893	30.343	15.458	41.364
50	12.601	10.522	17.628	32.691	17.665	41.292

number of rivers plus the sea, was set to 16. Initially, parameter d_{max} was set to 0.1 while the parameter C was 2. The total localization error was calculated as:

$$e = \frac{\sum_{i=1}^{N} \sqrt{(x_i - x_{i0})^2 + (y_i - y_{i0})^2 + (z_i - z_{i0})^2}}{N} \tag{11}$$

where $(x_i,\ y_i,\ z_i)$ is the location of the unknown sensor node, $(x_{i0},\ y_{i0},\ z_{i0})$ is the result of localization algorithm for one node, *N* is the number of all unknown sensor nodes.

The results of our proposed method and the method described in [42] (TLP) are presented in Table 1. Simulations were performed with the different errors ranges same as in [42]. As it can be seen, the error of estimated nodes locations is the smallest when the proposed WCA was used. In Table 1 avarage, minimum and maximum errors in 30 runs for ranging errors from 0% to 50% are reported. The proposed WCA obtained smaller localization error for all indicators and all simulations which leads to the conclusion that WCA is a superior method for the WSN localization problem.

5 Conclusion

In this paper we proposed the recent swarm intelligence water cycle algorithm for the localization problem in wireless sensor networks. The proposed method was compared to the particle swarm optimization method presented in literature. For all simulations, the WCA obtained better results, i.e. smaller localization error which allows to conclude that the proposed method is superior compared to the methods from literature. In future work, WCA algorithm can be tested for other WSN problems such as covering and deployment problems.

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