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Wireless Sensor Network Localization using Artificial Intelligence and Simulated Annealing Optimization

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***Abstract:** In recent years localization of nodes in wireless sensor networks (WSNs) has become one the main features of applications. In fact, this issue has been widely explored by the scientific community that proposed many approaches in order to localize network nodes. However, artificial neural network (ANN) can be used as an operating method. Therefore, we aim in this paper to select the best suited structure of ANN to localize in WSN using a meta-heuristic technique. To optimize this procedure, we use the Simulated Annealing (SA) algorithm. We constituted a network of ESP8266 modules to create our WSN topology as well as the training and the testing data to evaluate the performances.*

***Keywords:** Localization, WSN, Artificial Neural Network, Simulated Annealing, Wireless*

I. INTRODUCTION

Most of applications based on wireless sensor networks (WSNs) have come under spotlight as one of the upcoming applications in various areas, such as military surveillance, monitoring, robotics and many others. Hence, the localization of people or assets is one of the main features demanded in this field. Frequently, some processes such as telemedicine, control of temperature and humidity can be monitored in real-time at a different or the same geographic locating area. Therefore, the location information is primarily addressed in this regard.

GPS (Global Positioning System) is one of the easiest methods to keep up to date nodes to their respective positions. However, the low-cost profile, the low-power and the small form factor of the devices limit the GPS performances in indoor environment.

Several localization algorithms have been developed by Scientifics in order to overcome the WSNs localization issues. In fact, in literature we find analytical methods such as triangulation and trilateration to estimate coordinates of nodes within the network. However, some of the well-known methods utilizes the messages exchanged between WSNs' nodes in order to extract the connectivity information. One of the greatest examples in this class of algorithm is the Centroid algorithm [1].

In this paper, we propose the localization using artificial neural network (ANN) method implemented in a wireless sensor network. We perform the procedure of optimization through the Simulated Algorithm (SA) to obtain the best ANN operating point when locating within the WSN. Our proposed solution avoids the error procedure seen in [2]- [3] and allows more accuracy when we select the best structure of ANN.

Our present paper is organized as follows. The basic of artificial neural network theory and Simulated Annealing algorithm is presented in the next section. In section 3, We present our constituted WSN end discuss our results. Finally, we conclude our work in section 4.

II. BACKGROUND AND MOTIVATION

A. Artificial neural network

Neurocomputing first related article [4] created the first mathematical modeling for the artificial neuron. Furthermore, Donald Hebb developed a model of a neurophysiological hypothesis to describe by modeling the first ANN training method. The interconnection structures between artificial neurons (nodes) is called artificial neural network (ANN). The model of the nodes mimics by activation functions the biological neurons. Each of those nodes has a transfer function responsible for inputs to outputs mapping. In addition, each artificial node consists of a multiple input, weights and a signal output.

Basically, an ANN is an adaptative system which receives inputs set and provides an output by processing data. An ANN can have multiple or single layers in its structure known in the literature by the following designation: input layer, hidden layer (output layer). However, it is necessary to train the ANN before starting to use the ANN. By giving the correct answers for an input set and make adjustments to the weights based on the response of the network, this process performs. The training phase is completed when the ANN provides outputs under a specific limit of error. This type of training is known as supervised training.

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B. Simulated Annealing

Simulated Annealing algorithm is based on the annealing in metallurgy physical process [5]. Except it is able to propose and accept at a certain probability, it has similar principals as Hill Climbing.

Starting with a user given solution, the Simulated Annealing evaluates and finely modify it while performing. This solution is then kept as a new candidate in order to evaluate it and verify if it is a better solution than the previous. Once verified, Simulated Annealing algorithm accept it and consider it as the current solution. here is a probability of it to be also accepted based on the system present temperature and the cost of each solution in case of evaluating the solution as worse than the previous one. As shown below, (1) presents the Simulated Annealing Procedure formula.

$$P = \exp\left(-\frac{c(N) - c(P)}{t}\right) \quad (1)$$

Where:

P is the worst solution accepting probability

C(N) is the new solution cost

C(P) is the present solution cost

t is the temperature

While the Simulating Annealing algorithm is performing in a loop and after an arbitrary number of iterations, the temperature t is multiplied by a reduction factor. Consequently, the temperature will decrease and difficultly consider a worse solution as accepted. Thus, it utilizes one solution only and guide it to the best place of the space design.

III. EXPERIMENT WSN AND RESULTS

A. System Requirements

Since Wi-Fi is common in many buildings, it appears to be the more adequate technology to adopt. Therefore, our custom experiment WSN [6- 7] (Wi-Fi based) was developed according to the following requirement:

- Simplicity.
- Minimal infrastructure supporting.
- Restively inexpensive, since it is used for our study.
- Easy disassembly and quick deployment.

B. Experiment Setup

Our WSN consists of Wi-Fi modules (table I) deployed at location of interest. Each person or asset carrying an equipped device with Wi-Fi can be located.

Table-I: Experiment material

WSN Tags' nodes	ESP8266 modules
WSN locating nodes	ESP8266 modules
Network Manager	Computer

Locating Nodes scan every 20 seconds. At each scan period, we store the following data in the database:

- Scan time
- SSID of the tags
- A list of information of found nodes:
  - SSID
  - RSS values in dBm for distance estimation.
  - Transmission Power level in dBm for calibration purposes.

C. Results

The experiment scenario [8] was an indoor square area of 5x5 meters. This particular simulation area size was due to the test environment, which is approximately less than 6 meters. A total of 6 anchor nodes were placed (Fig.1) and configured for the experiment. A set of 8 grid ESP8288 modules configured as tags with known positions were used to collect the training data for our artificial neural network. For testing purposes, we use a set of 8 nodes within the area covered by training grid. Fig.2. below shows the location of training and testing nodes.

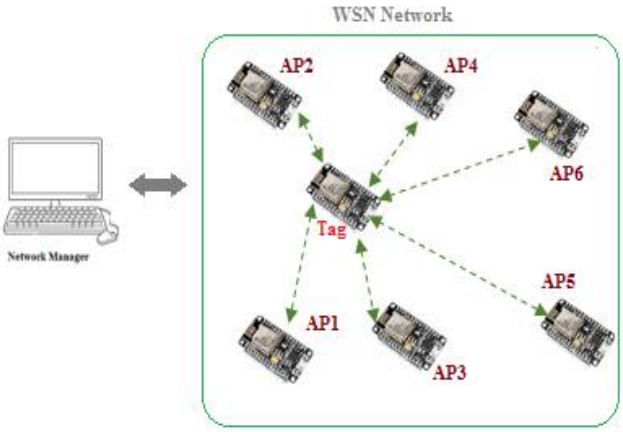

Fig.1. WSN network architecture

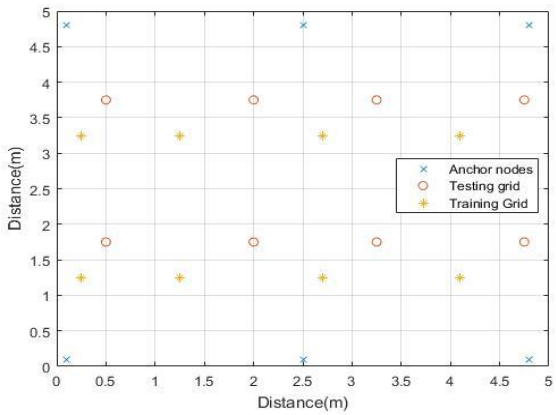

Fig.2. Training and testing grid for our Experiment

Each node of the training grid collects a set of samples. An input simple contains the following information: RSS values, (x, y) coordinates and SSID from all anchor nodes. In the experiment environment, the anchor nodes send 20 information, from which the first 10 are saved by every tag node in the training grid. This results in a data set with 80 samples (8 training nodes collect 10 input samples each). Due to the noised nature of the environment of experiment and eventually interferences or collisions, some information is not delivered. Hence, we send 20 information for tag nodes reception although we only save 10. One hop distance is used between each node and other. The optimization procedure starts performing when input data are gathered.

Then, by using the Simulated Annealing Algorithm, we allow to our ANN to modify its parameters which are: hidden layers number, number of nodes per hidden layer, and each hidden layer transfer function. Table II shows each of these parameters' boundaries.

Table-II: Our ANN parameters' boundaries

Parameter	Hidden layers number	Nodes number per layer	Each layer transfer function
Value	[0-4]	[1-17]	[Transig, Logsig, Purelin, Radbas]

Due to some computational and energy constraints of our experiment network, we select our own parameters' boundaries shown above although it can be customized. Therefore, we allow a small number of artificial neurons per layer and only a few hidden layers.

The Simulated Annealing Algorithm optimization requires, in order to begin the procedure, an initial Artificial neural network structure (initial solution). The SA is trained and tested with the acquired data to suggest a feedforward structure of ANN. These structures' cost function evaluation is performed by the use of root men square error (RMSE) between the estimated positions and the real positions of the unknown nodes. Formula (2) shows the calculation of the RMSE.

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}[(xi - xref)^2 + (yi - yref)^2] \quad (2)$$

Where:
n is the testing nodes number
x_i, y_i are the coordinates of the real nodes
x_{ref}, y_{ref} are the coordinates of the estimated nodes
i is the index of the node

All the calculations and optimizations at the network manager are done using:

- 8 Gb of RAM Memory
- Intel Core i5 1.8 Ghz

The processing time for the optimization using Simulated Annealing is about 20 minutes. Table III. Shows the best ANN found structure.

Table-III. Best of ANN structure using optimization

Parameter	Hidden layers number	Nodes number on input layer	Nodes number on hidden layer 1	Nodes number on hidden layer 2	Nodes number on input layer
Value	3	5	16	6	3

With:
Logsig: Input layer transfer function
Transig: Hidden layer 1 transfer function
Logsig: Hidden layer 2 transfer function
Purelin: Onput layer transfer function

As a result of using the best ANN structure, we obtain a RMSE of 0.57 meters, 1.81 meters as a maximum error and 0.061meters as a minimum error. The estimated positions and the real positions for this experiment are illustrated in Fig.3. We performed the optimization procedure at the network manger by using a PC, which makes it easier to integrate in other real application. This could be done only by changing the input data depending on the application field and apply the ANN weights provided when performing SA optimization.

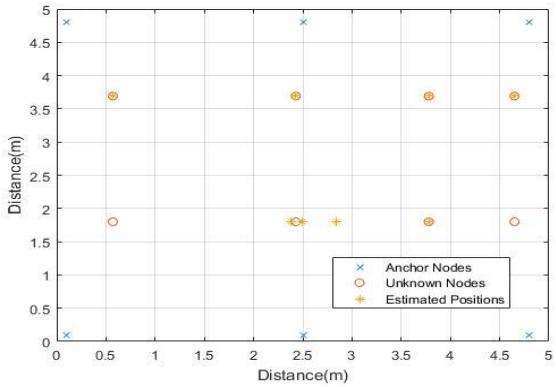

Fig.3. Real and Estimated positions data set for testing

IV. CONCLUSION

This paper presents an approach to localize within WSN constituted of ESP8266 modules using Artificial Intelligence. We perform the Simulated Annealing optimization as part of the learning machine of our ANN to find its best structure. We implement the ANN and manipulate an arbitrary initial structure by the SA optimization in order to tune the best performance of our WSN topology. Thus, we test this method in our indoor experimental environment of 5x5 meters with 6 anchor nodes. After the optimization procedure performed in approximately 20 minutes. As a result, we found the best ANN structure for our WSN through the Simulated Annealing algorithm, with a RMSE of 0.57 meters, 1.81 meters as a maximum error and 0.061meters as a minimum error.

This approach not only proves its effectiveness with those results but it reduces the dependency of the developer's experience when automatically selecting the best suited parameters for our ANN. Furthermore, localization accuracy significantly increased and required time for ANN adjustments reduced. Through the utilization of the best weights found after the optimization procedure, the found ANN can be used in various application, only by changing the training data to data collected through the use of nodes used in the field application.

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