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WSN기반의 인공지능기술을 이용한 위치 추정기술

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Localization Estimation Using Artificial Intelligence Technique in Wireless Sensor Networks

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ABSTRACT

One of the basic problems in Wireless Sensor Networks (WSNs) is the localization of the sensor nodes based on the known location of numerous anchor nodes. WSNs generally consist of a large number of sensor nodes and recording the location of each sensor nodes becomes a difficult task. On the other hand, based on the application environment, the nodes may be subject to mobility and their location changes with time. Therefore, a scheme that will autonomously estimate or calculate the position of the sensor nodes is desirable. This paper presents an intelligent localization scheme, which is an artificial neural network (ANN) based localization scheme used to estimate the position of the unknown nodes. In the proposed method, three anchors nodes are used. The mobile or deployed sensor nodes request a beacon from the anchor nodes and utilizes the received signal strength indicator (RSSI) of the beacons received. The RSSI values vary depending on the distance between the mobile and the anchor nodes. The three RSSI values are used as the input to the ANN in order to estimate the location of the sensor nodes. A feed-forward artificial neural network with back propagation method for training has been employed. An average Euclidian distance error of 0.70 m has been achieved using a ANN having 3 inputs, two hidden layers, and two outputs (x and y coordinates of the position)

Key Words : Anchor Nodes, Artificial Neural Network (ANN), Levenberg-Marquardt Algorithm, Beacons, Localization Estimation, RSSI values, Wireless Sensor Networks (WSNs). Networks (WSNs)

Ⅰ. Introduction

One of the most essential technologies in the twenty-first century is considered to be the field of Wireless Sensor Networks (WSNs). Recent advances in the micro electromechanical systems (MEMS) and wireless communication technologies have resulted in deployment of tiny, cheap, and smart sensors, capable of being networked through wireless links and to the internet. WSNs have a wide range of civilian and military applications; for example, environmental and vegetation monitoring, search and rescue operations[1], object tracking such as tracking patients[2] and doctors in hospitals, monitoring

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patients, military applications[3] and other industrial applications. Location based services are also commonly required by numerous sensor network applications.

Localization is the process of estimating the position of the nodes within a network and is a challenging part of many WSN applications. Many applications such as visual, thermal, acoustic, seismic, and other measured data require the location information to be attached with the data in order for it to be significantly assimilated and responded to. Automatic localization of the sensor nodes in this wireless network is a key enabling technology. The overwhelming reason is that a sensor's location must be known for its data to be meaningful. Node localization is essential for reporting the source of the events, supporting the group querying of sensors, routing, and for answering questions concerning the network coverage[4]. Over the years, various solutions to the problem of node localization have been reported by researchers[2,5-14]. The advantage of knowing the location information of sensor nodes are that it can be used to identify the location of an event of interest and responded to in a timely and efficient manner. A simple and straightforward solution to this is to equip each sensor node with Global Positioning System (GPS) receiver[15,16], which can be used to determine the exact location of the sensor nodes. However, this is not a feasible solution as sensor nodes are battery operated and GPS receivers consume quite a lot of energy. On the other hand, GPS does not work for indoor applications.

Since sensors are limited in hardware capabilities we pursue solutions that do not require any special ranging hardware at the sensor side to infer quantities such as range or angle of arrival estimates. In this paper, we propose a novel feed-forward artificial neural network (ANN) for 2D localization of the sensor nodes using the received signal strength indicator (RSSI) values of the beacons received from the three anchor nodes. Sensor nodes are freely equipped with RF modules for wireless communication, therefore no extra hardware will be required. Various different ANN training algorithm, such as Levenberg-Marquardt (LM), Bayesian Regularization (BR), Resilient Back-propagation (RP), Scaled Conjugate Gradient (SCG) and Gradient Descent (GD), are evaluated to obtain the best ANN model.

The remainder of the paper is organized as follows: In Section II, a brief overview of the related works in the field of node localization is presented. The proposed scheme, the experimental setup and data collection methods are presented in Section III while Section IV presents the evaluation of the results obtained and compared with other methods. Finally, Section V concludes the paper highlighting the major findings and recommending some future.

Ⅱ. Related Works

Over the years, various algorithms for node localization have been proposed targeting higher localization accuracy at low computational and hardware cost. Methods such as angulation, lateration, trilateration[5], multilateration and triangulation are often used in localization. Time-Of-Arrival (TOA), Time Difference of Arrival (TDOA)[11], Angle Of Arrival (AOA)[6,12] and the Received Signal Strength Indicator (RSSI)[17] are the range based algorithms. Localization schemes using directional antennas[13] have been used by many researchers where one or more nodes are used to measure the angle of arrival of the signal, which is used to calculate the position of the node with the unknown position. However, these special antennas are expensive and are not energy efficient for WSN applications. In [18], a 2D and 3D weighted centroid localization (WCL) algorithm is presented. This algorithm restricts the number of anchors involved by using an optimized threshold. The high-resolution range-independent localization (HiRLoc)[14] and modified HiRLoc[7] scheme used omni directional antennas. Recently, the use of artificial intelligence in WSNs[8-10,15] has been on the rise. The following paragraph briefly describes some of these algorithms.

A range free WCL for 3D WSN using Mamdani

& Sugano Fuzzy Inference System (FIS) is presented in [9]. In this method, the edge weights are computed based on the RSSI values via the Mamdani & Sugano inference system having 121 anchor nodes. Simulation results obtained showed an average localization error of 3.0 m. The authors in [8] proposed a 2D and 3D localization algorithm using a 10-10-3 neural network structure. The system had four inputs, with two hidden layers and two outputs for the 2D case. Hyperbolic tangent sigmoid and log sigmoid activation functions are used in the first and second hidden layers respectively. Simulations were carried out in order to evaluate the performance of the algorithm and an average localization error of 0.49 m was achieved for 2D localization with 95% of the times the error being less than 0.80 m.

In [19], the authors proposed a location estimation using extended Kalman filter in CSS WPAN. The post processing algorithms using extended Kalman filter for TOA and TDOA were studied. The frequency offsets of the mobile nodes are considered in the algorithm. The authors assumed 4 anchor nodes at fixed locations in 2D coordinate. The authors claimed that an error of less than 0.05 m was achieved for a 2.5 m square area.

Ⅲ. The Proposed Method

3.1 The Experimental Setup

The experiment for this research was carried out in a research laboratory of size 8.0 m x 6.4 m. The research laboratory contained equipments and furniture's such as computers, tables and chairs, and cabinets. The training and testing of a ANN requires a set of data in order to train and build a model and test its performance. The data in this case are the three RSSI values of the beacons received from the anchor nodes, which are used as the inputs, and their respective location or the coordinates, which are the targets or the outputs

The dataset was obtained by collecting the RSSI measurements of the beacons from the three anchor nodes at 96 (11 x 9 - 3) positions as shown in Fig. 1. The data points are 0.80 m apart. The grey points

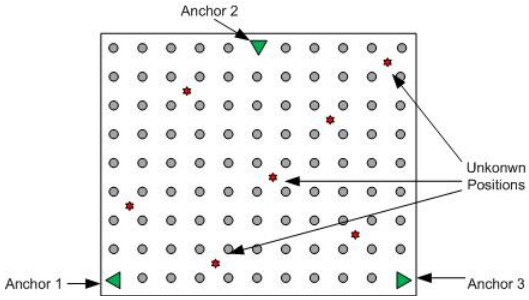

Fig. 1. Layout of the experimental setup laboratory

are the positions used to obtain the training data, considered as the known positions for the trained ANN model. The red points shown are used to test the ANN model obtained to evaluate its performance in predicting the location for unknown positions. While the positions of the three anchor nodes are shown in green.

3.2 Data Collection

The mobile wireless sensor nodes used in this experiment consists of Arduino Mega 2560 together with the XBee series 2 module, which has an air data rate of 256 kbps. These modules are IEEE 802.15.4 standard compliant and are called ZigBee. As for the anchor nodes, they only consist of the XBee series 2 modules operating on their own, without the use of any microcontroller. The XBee receiver has a -96 dBm sensitivity and with a 40 m communication range in indoor/urban environment. It has special IEEE 802.15.4-2003 hardware support such as the RSSI computation which has been fully utilized in this research.

The anchor nodes were configured in the attention (AT) mode while the mobile nodes XBee was configured to operate in the application programming interface (API) mode. Similar to opposing to sending data serially in the AT or the transparent mode, the decibel (DB) command is used to command the XBee explicitly in order to obtain the RSSI value of the most recent packet that has been received. The RSSI measurements made by the mobile node are serially transmitted to the computer, and the Docklight software[20] is used to read and record the serial data into a file as shown in the data collection setup in Fig. 2. The mobile node sends a message to the anchor nodes, upon which the anchor nodes send a beacon to the mobile node. The RSSI values of the three beacons received are recorded together with the location to form the data set for the training and testing of the proposed ANN. During the experiment, interference was present as other RF modules and WiFi was also operational.

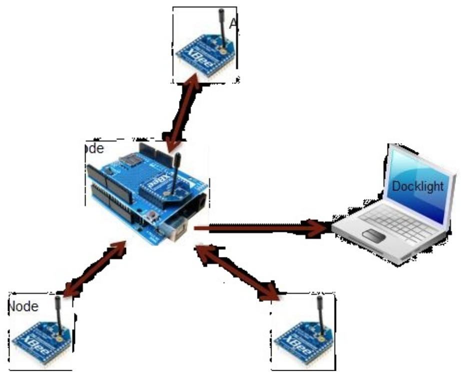

Fig. 2. Setup for collecting the data for training and testing

3.3 The ANN implementation

A practical method of learning discrete-valued, real-valued and vector-valued functions from examples is provided by neural networks. It is generally used for regression or classification problems and requires supervised learning that is, the inputs and the targets or the outputs are provided to learn the appropriate ANN model. A feed-forward multi-layer Perceptron (MLP) ANN is selected to be used for this research because of its best trade-off between the accuracy and memory requirements among the other types of neural networks. Since the ANN will be implemented on the mobile sensor node in real time for the purpose of localization, the computation complexity of the algorithm has to be kept as low as possible. Therefore, a neural network having the input and output layer, and two hidden layers has been employed. The input layer consists of 3 inputs, the output layer with 2 nodes, while the two hidden layers consist of 12 nodes each. This structure gave the best result given the constraints that the computational complexity be kept to a minimum in order for the proposed algorithm to be efficient. The inputs to the ANN are simply the RSSI values of the beacons received from the anchor nodes and the outputs are the x and y coordinates of the location of the mobile node. The final ANN structure obtained using Matlab implementation is shown in Fig. 3.

A linear activation function is used in the output layer while hyperbolic tangent sigmoid function has been used in both the hidden layers of the proposed system as shown in Fig. 3. The final ANN model selected was obtained using the LM learning algorithm as it required fewer amounts of training time and memory requirements compared to other learning algorithms evaluated, and produced acceptable localization results. The input and output data structure used for training the ANN model is shown below, where Aijrepresents the jthanchorsRSSIvaluefortheithsamplewhilexi and yi are the x and y coordinates of the ithsampleandn is the total number of samples.

$$input = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ \vdots & \vdots & \vdots \\ A_{n1} & A_{n1} & A_{n3} \end{bmatrix} \quad output = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \vdots & \vdots \\ x_n & y_n \end{bmatrix}$$

Upon selecting the ANN model to be used, the ANN weights and bias parameters were obtained from the model and the model was implemented on the mobile node that is implemented using C language on the Arduino platform. The implementation of the ANN is given by equation 1, where A is the three dimensional input vector consisting of the RSSI values of the beacons

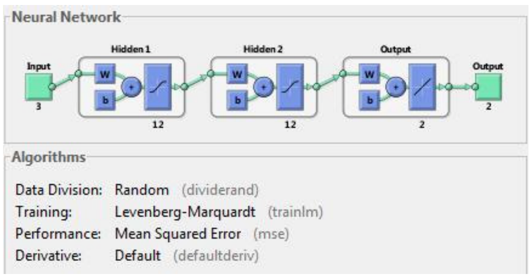

Fig. 3. The structure of the proposed feed-forward ANN

received from the three anchor nodes, $w_k^{(l)}$ is the weight vector of k^{th} node of l^{th} layer, $b_k^{(l)}$ is the bias vector of k^{th} node of l^{th} layer. Other programming language or platform can also be used for the implementation of the ANN.

$$\begin{bmatrix} x \\ y \end{bmatrix} = w_k^{(3)} \cdot \tanh[w_k^{(2)} \cdot \tanh(w_k^{(1)} \cdot A + b_k^{(1)}) + b_k^{(2)}] + b_k^{(3)}$$

3.4 Application

The study of ship-borne WSN is continuously increasing and consists of two aspects; study of communication of WSN on shipboard and using WSN to monitor work environment on shipboard[21] (for example, monitoring the temperature of the engine room). Currently, Radio Frequency Identification (RFID) and GPS-based technologies are being utilized in ports and terminals as the most advanced logistic solution for identification and localization of shipping containers in ships and yards. However, there are limitations to these technologies and real time localization becomes difficult. Therefore, this paper proposed a non-conventional approach for determining the position of the containers in real time ship IT environment. The proposed method is a range free method, which estimates the location of the containers, based on the information of the anchor nodes linked to the targets. Each container will be equipped with sensor nodes, which will communicate with the anchor nodes to estimate its position. The container sensor nodes will have all the necessary information about the content and environment of the container together with its location. Therefore, this localization method can be used for monitoring the environment and the state of the cargo on shipboard together with is location (especially for dangerous cargo) in order to improve the safety of navigation and achieving the goal of early warnings. In case of any emergency, it is very essential to know the position of the container so that emergency measures can be taken within the shortest possible time. The method can also be used for other WSN applications requiring the position of the node.

Ⅳ. Results and Discussion

The Matlab software was used for training and testing the ANN. Different activation functions with different number of layers and nodes were tested and the best optimal solution was chosen to be a network with three layers having a 12-12-2 structure that is having 12 nodes each in the hidden layers and 2 nodes in the output layer. And the activation functions used are the hyperbolic tangent sigmoid function for the hidden layers and linear function for the output. As mentioned earlier, five different ANN learning algorithms namely LM, BR, RP, SCG and GD have been evaluated. The training time of these learning algorithms were evaluated and are shown in Fig. 4. The best performance for node localization was shown by LM and BR learning algorithms as shown in table 1. However, the BR learning algorithm takes a lot of time and has high memory requirements compared to the LM learning

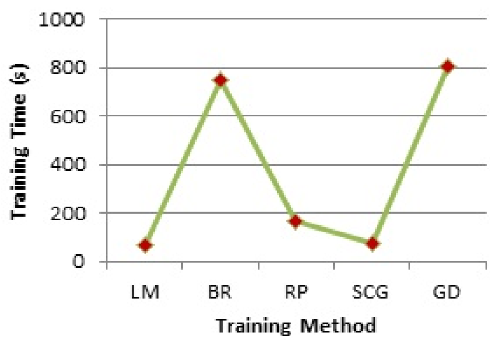

Fig. 4. Time taken for training the ANN with different algorithms

Table 1. Localization performance with different learning algorithms

Learning Algorithm	Average Localization Error (m)	Maximum Localization Error (m)
LM	0.87	1.87
BR	0.85	1.92
RP	0.98	2.06
SCG	1.12	2.13
GD	1.26	2.16

algorithm. Therefore, the LM learning algorithm was selected to be used to obtain the best ANN model.

The data structure used for training and testing is mentioned in the previous section. A total of 2400 samples containing data from the 96 points with 25 samples taken for each point have been used. The data is first randomly arranged and then divided into the training, validation and testing sets. For training and testing, 70% of the data was used for training, 15% of the data for validation and 15% of the data was used for testing. The performance of the system was evaluated based on the average Euclidian distance error, given by equation 2. Where n is the number of test data samples, (x_{ai}, y_{ai}) is the actual and (x_i, y_i) is the estimated coordinates of the mobile node at the l^{th} test data set.

$$average\,error = \sum_{i=1}^{n} \frac{1}{n} \sqrt{(x_i - x_{oi})^2 + (y_i - y_{oi})^2} \qquad (2)$$

The average and maximum error obtained are shown in Fig. 5. The average error for the location estimation at the known positions using the proposed ANN was 0.40 m. After selecting this final ANN model, it was implemented on the mobile node for testing the performance in real time. The test was carried out at seven different unknown locations as shown in Fig. 1. These locations were not used in the initial training of the ANN. The location estimation at each unknown test point was carried out several times and the average error of 0.87 m was obtained as shown in Fig. 5, marked as average error (unknown positions) represented in green. The maximum error resulting from the overall testing using known and unknown positions was 1.84 m. Furthermore, 94% of the time the localization error was less than the average error (unknown positions) of 0.87 m.

The results obtained using the proposed feed-forward ANN is quite promising for applications requiring location accuracy of within a meter. Only 6% of the times the localization error was greater than 0.87 m. However, this value can be decreased by choosing a bigger neural network structure at the cost of extra computation power and

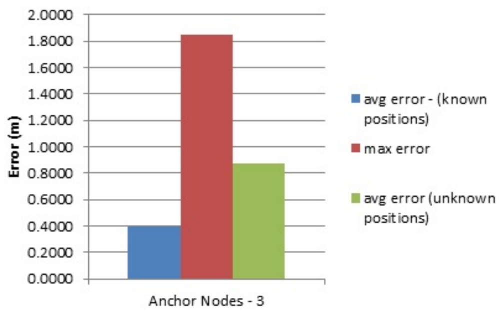

Fig. 5. The average and maximum localization errors of the proposed ANN

energy. In Table 2, the proposed algorithm is compared with other related localization algorithms. As it can be seen from the table, the proposed algorithm is evaluated in real time environment where as the other methods present the results from simulations. The proposed 12-12-2 feed-forward ANN gives a accuracy that is higher than the 2D-WCL[18], which used 100 anchor nodes for localization and the Mamdani and Sugano FIS[9] system utilizing 121 anchor nodes. Using higher number of anchor nodes mean message exchange take place at the mobile node for localization, which directly results in an increased energy consumption thus resulting in reducing the battery life of the sensor node. The neural network method proposed by authors in [8] is also promising as only a 10-10-3 neural network structure is used to achieve an average localization error of 0.49 m using four anchor nodes. However, the results are only evaluated using the simulation environment. Although the average localization error of the

Table. 2. Comparison of different localization algorithms

Localization Algorithm	Average Localization Error (m)	Number of anchor nodes	Implementation Environment
2D-WCL[18]	> 3.00	100	Simulation
Mamdani and Sugano FIS[9]	3.00	121	Simulation
Neural Network (3D)[8]	0.49	4	Simulation
Proposed ANN (2D)	0.87	3	Real Time

proposed ANN system is higher than that compared to [8], the proposed system is evaluated in real time environment and uses one less anchor node. Also, the average localization error obtained from known positions is comparable with that of [8].

Ⅴ. Conclusion

A feed-forward ANN for node localization for WSNs in 2D environment is presented and an average localization error of 0.87 m has been obtained by performing experiments in real time environment. The RSSI values of the beacons received from three anchor nodes are used as the input to the proposed ANN for estimating the position of the mobile node. The advantage of using the RSSI values for localization is that it does not require any additional hardware as the sensor nodes are equipped with RF modules. A two way message exchange is used for obtaining the RSSI values for the input. This is to prevent unnecessary message exchange as the mobile node only proceeds to estimate the location when needed by requesting the anchor nodes to send beacons.

Currently, only the RSSI values of the beacons received from the anchor nodes are used. However, it is recommended that the RSSI values of the beacon request signal received by the anchor nodes also be utilized as it might result in better localization accuracy. Further work will be carried out to evaluate this. For applications where online training is done, the LM algorithm is recommended to be used for training the ANN as it is fast and has low memory requirements compared to other learning algorithms that have been evaluated. Applications where the training time is not important and memory requirement is not a factor, the BR algorithm can be used.

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