Performance Evaluation of Lateration, KNN and Artificial Neural Networks Techniques Applied to Real Indoor Localization in WSN

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***Abstract*-In Wireless Sensor Networks, several protocols and algorithms seek to prolong the network lifetime; among them, the localization algorithms are used as an accessory to provide the smallest distances for sending messages. This paper compares the Lateration, KNN and ANN as localization techniques to estimate planar coordinates using the RSSI in an indoor environment using a real WSN based on IRIS motes. The results show that a well worked out ANN is superior to Lateration and KNN.**

Keywords-Wireless Sensors Network; RSSI; Artificial Neural Network; localization algorithms; Lateration; KNN.

I. INTRODUCTION

Wireless Sensors Networks (WSNs) have many applications in various segments of society, including areas such as military surveillance, industrial and agricultural monitoring and residential automation [1]. They operate with low-power consumption devices, low hardware processing, and higher autonomy [2].

There are various protocols, algorithms and techniques in which the objective is to extend the network lifetime as security systems [1][2], data fusion [3], tracking [4], etc. Several metrics are approached to improve network routing accuracy considering reducing energy consumption. The sensor node localization in WSN is noteworthy as one of the more effective metrics to reduce energy consumption, since the longer the distance the greater the energy consumed by a node for routing information.

GPS (Global Positioning System) usage is a very popular method when it comes to sensors localization. However, it has some disadvantages in WSN, such as the use of up to four satellite signals to achieve a good localization, the need of high power consumption due to the receiving of satellite signals communication and the high cost of using a GPS in each sensor node [3]. Leaving this method aside, other alternative techniques are able to compose a WSN localization system [4].

Some well-known localization techniques are Lateration, Nearest Neighbor (NN), K-Nearest Neighbor (KNN), Min-Max [4], ANN [5], Kalman Filter [6], Time of Arrival (TOA) [3], Time Frequency of Arrival (TFOA) [7] and Least-Square Support Vector Regression (LSSVR) [8].

The Lateration, Min-Max, KNN and ANN is a set of techniques that use the Received Signal Strength Indicator (RSSI) for estimating node localization in WSN. It is a measure of the signal power on the radio link while a message is being received. Thus, the power of RSSI is inversely proportional to the distance (1).

Featuring the RSSI, it is possible to:

- Calculate in matrix the location of each point (Lateration),
- Estimate the coordinates as weights in the arithmetic average of its nearest neighbors (KNN),
- Insert inputs in an Artificial Neural Network (ANN) or,
- Obtain the geographical location of a network node using other techniques and filters.

This paper presents an experimental evaluation that compares the following techniques: Lateration [9], KNN [10] and ANN designed for localization. All the experiments were performed based on a set of RSSI collected and applied to localization techniques in the study in a real environment.

The paper is divided into seven sections including this introduction. In Section 2, a survey of related work is performed, showing localization techniques without the use of GPS, using the RSSI as a metric for estimating planar coordinates. In Section 3, the methodology presenting the test environment, hardware and software is discussed, and a brief introduction about the Lateration, KNN and ANN techniques is given. Section 4 presents the benchmark results of comparing the Lateration, KNN and ANN techniques. Later, in Section 5, we present our final remarks, followed by our suggestions for future work in Section 6.

II. RELATED WORKS

This section introduces some researches about performance evaluations of WSN, highlighting comparisons between the localization techniques.

Priwgharm and Chemtanomwong [4] performed a comparative study of the Lateration, Min-Max, NN and KNN techniques in an experimental indoor environment measuring 3x3 meters using XBee modules. The article shows Lateration as the technique with a smaller margin of error than the KNN technique.

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Rice and Harle [11] compared the localization algorithms Non-Linear Regression (NLR), Iterative Non-Linear Regression (INLR), Least Squares (LS), Random Sample Consensus (RANSAC) and Trilaterate on Minima (ToM) is shown. Data were collected from real environments in an area of 550 m^2. The radios use Ultra-Wide Band (UWB) (IEEE 802.15.4a) in their physical layer for transmitting and receiving signals. The INLR (Iterative Non-Linear Regression) technique gives the smallest number of estimate of location errors.

Shareef et al. [12] made a comparative work in a real environment is performed among several ANN based on methods such as Radial Basis Function (RBF), Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), Position-Velocity (PV), Position Velocity Acceleration (PVA) and Reduced Radial Basis Function (RRBF). These methods evaluate the location errors in centimeters using these techniques in a 3x3 meters indoor environment. However, they do not compare the performance between some of the ANN methods with the common localization methods applied in a real environment; their results do not show a benchmark among the solutions.

Tian and Xu [13] performed in a real environment a comparison between a Multi-Layered Perceptron Neural Network (MLPNN) model and two Kalman Filter models, namely PV and PVA techniques. The environment measures 3x3 meters, marked in grid spacing of 0.30 meters with four beacon nodes located in the vertices of a square. The mobile nodes were placed on each intersection of the grid to collect the data. The experimental results indicate that the MLPNN neural network has the best performance, but there is a potential retraining or redesign cost associated with the use of MLP, which is not associated with the Kalman's filter [13]. This work only compares Kalman's filter with MLPNN, not with tests performed using mathematical techniques.

Rahman et al. [14] made a simulation is performed in an environment measuring 200x200 meters, where they implement an ANN with the Levenberg-Marquardt algorithm [14] using an error minimization function. The simulation shows that the location accuracy improves with the increase of grid sensors density and Access Points (APs). The work is restricted to simulation and does not present the benchmark among the techniques analyzed, disadvantaging a clearer comparative preview.

Langendoen and Reijers [15] simulated Lateration and Min-Max algorithms together with the sum of the distances, DV-Hop and Euclidean algorithms. They perform only simulation and it is described as an ideal environment, without discussing the effect of path loss or variable depending on the Lateration.

Zheng and Dehghani [16] made a new ANN method known as Location Neural Network Ensembles (LNNE) is compared with DV-Hop and a Localization Signal Neural Network (LSNN). The experimental results demonstrate that LNNE consistently outperforms the other three algorithms in localization accuracy. This work employs a simple scenario controlled by simulation, but it does not perform a validation of the theoretical aspects in real environments.

Maheshwari and Kemp [17] compared three methods of localization, namely Optimal Multi-Lateration (OML), Sub-optimal Blind Trilateration (SBT) and Geometric Dilution of Precision (GDOP). They provide the benchmark in terms of achievable accuracy. However, they only compare the performance among Lateration variants and not techniques of a different nature, and their approach only uses simulation without conducting any real experiment.

According to an analysis of related work, many of the studies involve the use of Lateration or some of its aspects [4][11][15][17], while other studies [12][13][14][16] compare the various topologies of ANNs. An experimental approach is presented in [4], in which Lateration shows the best results compared with three other techniques (KNN, NN and Min-Max). Based on the results presented in the above references, this paper conducts a performance evaluation using the two best methods presented in [4] (Lateration and KNN) to compare with ANN.

Since most of the current works are restricted to the use of simulation, and experimental works are much scarcer, the main contribution of this paper consists in establishing a practical comparison between some common classification techniques employed to use locating sensors in real environments.

III. METHODOLOGY

This section presents the methodology to acquire the data and characteristics from the environment of the experiment, besides the approach to determine the architecture of the artificial neural network used in this research.

A. Environment

The tests were conducted in an indoor environment grid of 12x12 meters, as seen in Fig 1. The beacon nodes (red) are positioned in the corners of the scenario, points (0, 0), (0, 12), (12, 0) and (12, 12), and the nodes to be localized (blue) are positioned in the internal area of the grid.

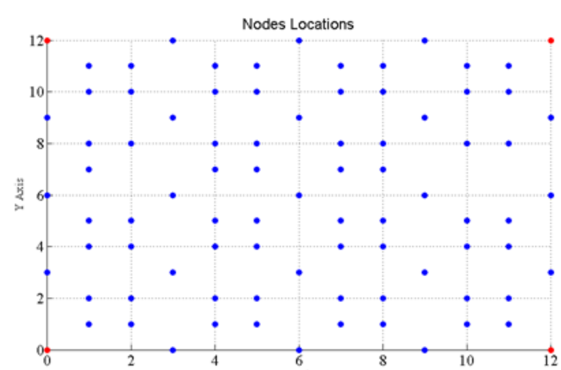

Fig. 1 Points in which the RSSI signals are collected through the target node

This area is configured in an indoor environment free of obstacles or barriers that may degrade the radio signal propagation.

B. Hardware

For real tests, this research uses the IRIS motes of MEMSIC, which implement the IEEE 802.15.4 radio standard in the range of 2.4 to 2.48 GHz and a maximum data rate of 250 kbps. This hardware can transmit data at a distance of up to 500 meters in direct view. The IRIS hardware is based on XM2110CB radio and ATmega1281 CPU, both from ATMEL. To support the WSN node gateway, a MIB520 is used, which consists of a USB adapter that enables two serial communications, one for control and one for data.

C. Middleware

We used the TinyOS platform as a software component running on the sensor nodes. This is an operating system with open source BSD license devices designed for low power consumption such as WSN, ubiquitous computing, personal networks, home automation and industrial [18].

A Java-based RSSI application was developed to extract the data in real time. The data are recorded in a file with the following fields: actual location, node identifier and the RSSI value obtained by target node.

D. Lateration Algorithm for Localization

A target node receives a message from each beacon node, in which it can get the value of the power in dBm from the signal, as shown in (1), or as a function of distance (in meters) according to (2).

$$RSSI[dbm] = -10 * n * \log(d)_{10} + A \quad (1)$$

$$d = 10^{\frac{Rssi-A}{-10*n}} \quad (2)$$

The values of A (1 meter RSSI distance) and n (path loss) are estimated before testing localization, thereby obtaining the value of the distance in meters from the anchor nodes to the target node. For each message received by an anchor node, the distance d_i is determined from the (3).

$$d_i{}^2 = (x - x_i)^2 + (y - y_i)^2 \quad (3)$$

where x and y are coordinate values related to the target, x_i and y_i are coordinate values related to the i-th beacon node, and d is the distance between the target and the i-th beacon node.

For each i visible anchor nodes, there will be one distance and one equation as a function of x and y coordinates. They can be summarized in matrix form as shown in (4). B is the estimated localization vector from coordinates x and y. Equations (4) – (7) are found in [4].

$$\mathrm{B} = \mathrm{A}\,\mathrm{X}^{-1} \quad (4)$$

where,

$$\mathrm{B} = \begin{bmatrix} x \\ y \end{bmatrix} \quad (5)$$

$$A = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 - d_1^2 + d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 - d_{n-1}^2 + d_n^2 \end{bmatrix} \quad (6)$$

and,

$$\mathrm{X} = \begin{bmatrix} 2(\mathrm{x}_1 - \mathrm{x}_\mathrm{n}) & 2(\mathrm{y}_1 - \mathrm{y}_\mathrm{n}) \\ \vdots & \vdots \\ 2(\mathrm{x}_{\mathrm{n}-1} - \mathrm{x}_\mathrm{n}) & 2(\mathrm{y}_{\mathrm{n}-1} - \mathrm{y}_\mathrm{n}) \end{bmatrix} \quad (7)$$

E. KNN Algorithm for Localization

KNN is one of the most popular methods of classification due to its simplicity and reasonable effectiveness. It requires the assembling of a specific model and has shown good performance for the classification of various types of data [19].

As shown in (1), the RSSI is inversely proportional to the distance. To calculate the distance, we use the largest RSSI values that correspond to the closest nodes. Subsequently, we calculate the weighted average to estimate the values of x and y coordinates from the target node, as shown in (8).

$$\begin{cases} x = \frac{\sum_{i=1}^{i\leq k}(RSSI_i * x_i)}{\sum_{i=1}^{i\leq k} RSSI_i} \\ y = \frac{\sum_{i=1}^{i\leq k}(RSSI_i * y_i)}{\sum_{i=1}^{i\leq k} RSSI_i} \end{cases} \quad (8)$$

where x and y are the coordinate values of the target node, $RSSI_i$ is the power value of the received signal from the i-th node, x_i and y_i are fixed coordinate values of the i-th node, k is the limit number of neighboring nodes. Then, the weighted average is calculated to estimate the values of the x and y coordinates of the target node.

F. Artificial Neural Network

Our application of ANN used for the localization of nodes in WSN is accomplished through the acquisition of RSSI from the messages sent from each node. Subsequently, these data are used to train and validate the network.

For each location point, the mean and standard deviation are calculated to identify the 10% worst samples. With this, only accurate samples are used to train the ANN.

To train the ANN, the collected points (x, y) are normalized maintaining those data output values between 0 and 1.

To define the architecture of the ANN, several tests are done to achieve a satisfactory configuration of the ANN, i.e., number of hidden layers, number of neurons in each layer, activation function for each layer or neuron and training algorithm.

The architecture used in the ANN is a feed-forward network with five layers: the input layer with 4 neurons (RSSI values of each beacon nodes), three hidden layers with 10 neurons in each and the output layer with two neurons (x and y). The learn rate used is 0.7. The parameters of the ANN are summarized in Table 1.

TABLE I. ANN CONFIGURATIONS

Training	SARPROP
Activation Function for output layer	Symmetric Gaussian
Activation Function for hidden layers	Symmetric Cosine
Training error function	Linear
Training stop function	MSE
Input Layer	4 neurons + 1 bias
Hidden Layers	3 layers with 10 neurons + 1 bias for each
Output Layers	2 neurons
Total neurons	40

The network training is preceded by the choice of training method, activation function, number of hidden layers and the number of neurons in each layer. The training stops after 500 000 epochs.

IV. RESULTS

The absolute values of positioning errors in the coordinates x (x_{error}), y (y_{error}) and the Localization error (l_e) are used as a metric for comparing the techniques. The position error is the distance between the actual point and the estimated value as shown in equations (9), (10) and (11), respectively.

$$x_{error} = |x_{real} - x_{estimated}| \quad (9)$$

$$y_{error} = |y_{real} - y_{estimated}| \quad (10)$$

$$l_e = \sqrt{(x_{error})^2 + (y_{error})^2} \quad (11)$$

To compare the results between Lateration, KNN and ANN techniques, we use the equations (12) and (13) to generate the graphs of the benchmark shown in Figs. 3 and 4, respectively.

$$bm_{ANN\times LAT} = 100 * \frac{l_{e_{LAT}} - l_{e_{ANN}}}{l_{e_{LAT}}} \quad (12)$$

$$bm_{ANN\times KNN} = 100 * \frac{l_{e_{KNN}} - l_{e_{ANN}}}{l_{e_{KNN}}} \quad (13)$$

where,

$bm_{ANN\times LAT}$: Benchmark of ANN versus Lateration
$bm_{ANN\times KNN}$: Benchmark of ANN versus KNN
$l_{e_{ANN}}$: Localization error obtained from ANN in meters
$l_{e_{LAT}}$: Localization error obtained from Lateration in meters
$l_{e_{KNN}}$: Localization error obtained from KNN in meters

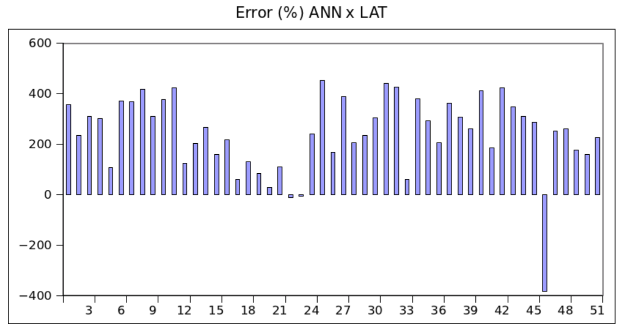

Fig. 2 Percentage comparison between the Artificial Neural Network and Lateration

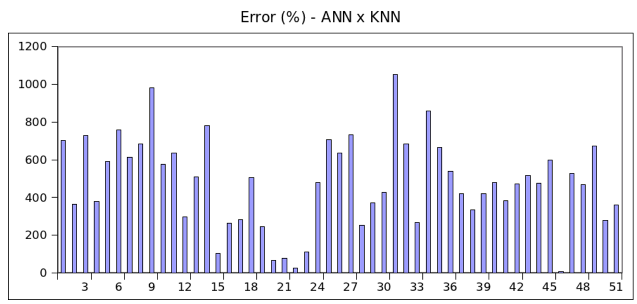

Fig. 3 Percentage comparison between the Artificial Neural Network and KNN

In Fig. 2, we can observe the comparison between ANN and Lateration, in percentage, where positive values indicate that ANN has better results than Lateration. Similarly, Fig. 3 shows a comparison between ANN and KNN. To illustrate these graphs, only 50 points were selected from a total of 255 used to estimate the localization (blue points in Fig. 1). Negative values occur whenever the ANN technique does not yield better results in the comparison.

The ANN achieved better results in the localization with average 232.43% better than Lateration and 470.45% better than KNN. Table 2 shows the percentage of cases in which each technique has the best performance for the aforementioned metrics.

The x and y values were estimated to apply filters in future works that allow reducing the error estimated by a coordinated reducing of the distance error.

The data in Table 2 show that ANN obtains 76.0784% and 79.6078% of the best samples in the x and y coordinates, respectively, when compared to Lateration. In the comparison of KNN and ANN, Table 2 shows that 85.8824% and 88.6275% of samples have better results for x and y coordinates, respectively. Therefore, the ANN shows better results when compared with Lateration and KNN.

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TABLE II. BEST PERFORMANCE: ANNxLAT AND ANNxKNN

Comparison	ANN x LAT		ANN x KNN	
Metric	*%ANN*	*%LAT*	*%ANN*	*%KNN*
x	76,0784	23,9216	85,8824	14,1176
y	79,6078	20,3922	88,6275	11,3725
Localization error	94,902	5,098	98,0392	1,9608

When we consider the distance of the estimated localization and real localization, ANN has better results than Lateration and KNN, i.e., the ANN estimates the localization near the real localization in 94.902% compared to Lateration and 98.0392% compared to KNN.

Table 3 shows the average (Avg) and variance (Var) of the positioning error of each technique. The mean and variance of the positioning error in the ANN are lower than those calculated for Lateration and KNN.

TABLE III. MEAN AND VARIANCE OF THE POSITION ERROR IN METERS FOR EACH TECHNIQUE

	LAT		KNN		ANN	
	Avg	Var	Avg	Var	Avg	Var
error *x*	1,76	1,27	2,68	3,55	0,80	0,51
error *y*	2,02	1,34	3,77	4,68	0,88	0,88
error distance	2,94	1,18	5,01	4,49	1,30	1,12

TABLE IV. QUANTITATIVE ANALYSIS OF EVERY 1 METER IN DISTANCE ERROR

Localization error	%LAT	%KNN	%ANN
$0 \leq l_e < 1$	5,09	1,96	48,62
$1 \leq l_e < 2$	19,21	6,27	29,80
$2 \leq l_e < 3$	22,74	8,23	15,29
$3 \leq l_e < 4$	35,29	14,50	3,52
$4 \leq l_e < 5$	17,64	21,17	2,74
$l_e \geq 5$	0	47,84	0

In Table 4, samples are organized by zones of error. For errors which are smaller than 1 meter, the ANN shows the best results with a large advantage because 48.62% of the estimated positions' locations are within the lower zone of error, i.e., error < 1 meter.

Figs. 4 and 5 show some samples of estimated locations. Each real point is illustrated by a square connected to its three estimates by a dashed line.

Fig. 4 shows samples located in the periphery of the scenario. With this figure, we can observe the behavior of these techniques near the borders. Fig. 5 shows the internal points situated in the innermost region of the experiment.

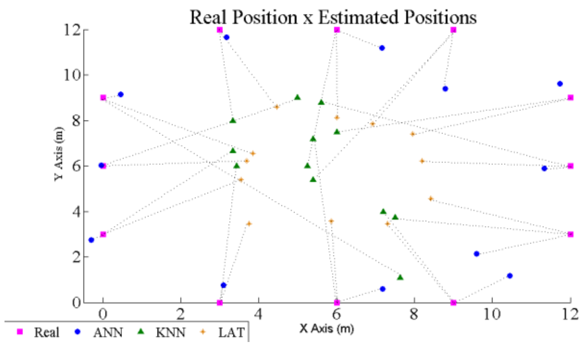

Fig. 4 Real and estimated positions by technique for peripheral points

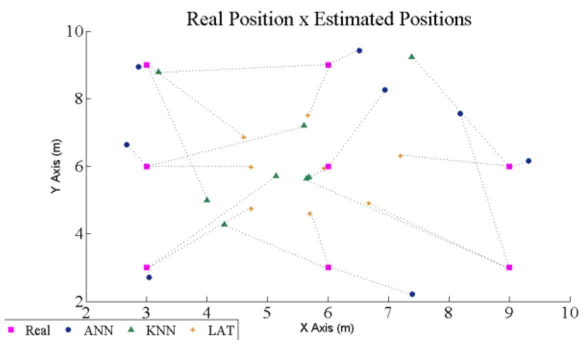

Fig. 5 Real and estimated positions by technique for internal points

To compare the localization techniques presented here, we estimate the size of the accumulated error indicating how each technique deviated from the actual value for each record as illustrated in Fig. 6.

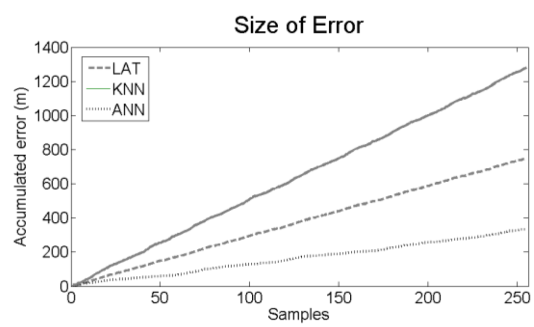

Fig. 6 Size of accumulated error (m)

Fig. 6 shows the near-linear behavior resulting from the accumulation of error over the samples. The final accumulated error of Lateration and KNN is 225.05% and 383.61% greater than the final accumulated error observed in ANN, respectively.

V. FINAL CONSIDERATIONS

The application of a neural network to resolve the localization problem shows satisfactory results in the estimation of a node within the limits of the beacon nodes. This method had lower mean and error variance when compared to the techniques of Lateration and KNN, therefore having increased stability. However, the number of inputs is fixed and directly related to the number of beacon nodes, resulting in the need to retrain for different amounts of network beacon nodes.

The Lateration is a technique for easy adjustment, depending on the number of beacon nodes maintaining stability similar to ANN. This technique requires an accuracy of the path loss of the environment and the value of the constant *A*, otherwise, the error can be increased and may exceed the expected limits.

In this experiment, the KNN technique was performed by the weighted sum of each coordinate by dividing the sum of their weights. In KNN, the estimated location tends to be found within the boundaries of the scenario, due to the weighted sum of RSSIs from their neighbors.

In [4], the performance evaluation indicates the Lateration technique has better precision, followed by KNN. In this study, both techniques were compared to ANN for localization. We observed that ANN had lower error and, consequently, better precision in locating the target node, as show in the analysis of the mean and variance of the error for both x and y coordinates and localization error, creating good reliability in the use of ANN compared to classical techniques for locating wireless sensor networks.

VI. FUTURE WORK

As future work, we intend to perform the target tracking in real time by applying this current artificial neural network to perform this task, test for different amounts of beacon nodes and test these techniques with other hardware, and apply filters to minimize error for coordinate and distance.

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