World Scientific Research Journal Volume 6 Issue 10, 2020
ISSN: 2472-3703 DOI: 10.6911/WSRJ.202010_6(10).0040

3-D Localization in WSNs Using UAVs

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Abstract

Many algorithms of Wireless sensor networks (WSN) are supposed to be bound up with the geographic information of the sensor nodes, such as routing protocol, which indicates the necessity of sensor nodes localization. In this work, a GPS-equipped UAV that moves along the predetermined route is employed to sends signals periodically and the sensor nodes with unknown positions receive them. And the approximate distances between UAV and sensor nodes are obtained via the Received Signal Strength Indicator (RSSI) technique. To alleviate path interference, reduce error, and optimize the localization algorithm, the neural network trained by a machine learning algorithm is utilized. Then, comparisons between the localization algorithm in this work and algorithms of other researches are made and indicate that the neural-network-based method that we proposed has the best performance.

Keywords

3-D localization, UAVs, WSNs, RSSI, Random Forest, SLFN.

1. INTRODUCTION

The localization system is the core component of Wireless Sensor Network (WSN), through which the identification and correlation of target event and its data information, nodes addressing, management, and query in a specific area can be implemented. The indispensability of the localization system can be demonstrated via its function of the appointment of the events location and data information collected, and even its promoting effect on the improvement of the performance of some routing algorithms, such as Dynamic and Scalable Tree.

The localization problem in networks can be quantified as the physical location of sensor nodes, such as latitude, longitude, and altitude. Generally, the localization algorithm model of WSN is to position a group of network nodes, whose location coordinates are unknown, based on a limited number of nodes with known coordinates.

Nevertheless, problems such as restricted energy, fragile reliability, large-scale and random deployment of sensor nodes, the limited communication range of wireless modules existing in sensor networks put forward high requirements for localization algorithm and technology, including the aspects of self-organization, energy efficiency, and distributed computing, which will be the reference and evaluation standard to select the most appropriate algorithm.

At present, UAVs have been utilized to research the technology of two-dimensional positioning in WSN. The goal of this work is to study the application of UAVs in the 3-D

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localization technology of sensor networks and to optimize the positioning algorithm by using the neural network trained by several machine learning algorithms, to improve the accuracy. The conversion from 2-D positioning to 3-D one is not only as simple as the increase of dimension. The specific contents of 3-D localization technology are described later, including the establishment of UAVs and their deployment model, the channel model of the conversion from signal strength into the distance, the comparison and selection of localization algorithms, and the performance evaluation.

The remainder of this paper is organized as follows. Section 2 covers the literature review on distance estimation and localization algorithm. Section 3 describes the system model, including UAV deployment and neural network implementation. The performance analysis is given in Section 4 in respect of simulation settings, wireless communication channel models, distance, and location estimation. At last, the research conclusion and future work are summarized in Section 5 and Section 6.

2. BACKGROUND AND RELATED WORK

Our proposed localization method includes two separate parts, UAV-assisted distance estimation, and neural-network-based localization estimation algorithm. This section highlights existing work on both of them. Subsection 2.1 presents a brief development process of mobility-assisted localization. Subsection 2.2 describes the background of traditional localization estimation algorithms and differentiates these traditional localization algorithms from our proposed neural-network-based localization technique.

2.1. Mobility-assisted Localization

The localization of a node with the unknown position is reckoned based on the information of anchor nodes with the known ones. In the distance-based positioning technology, the location of unknown nodes is estimated by using some physical characteristics of the measured signal, namely the time of arrival (ToA) [1], angle of arrival (AoA) [2], time difference of arrival (TDoA), or received signal strength indicator (RSSI) [3], [4]. Among these parameters, RSSI is the most commonly used in several localization techniques for a variety of reasons, such as the simplicity of the parameters. In contrast to AoA measurements and time-based measurements that require additional hardware and technology, RSSI is available from almost all wireless hardware. Thus, RSSI-based localization is a cost-effective solution for most IoT applications. To improve positioning efficiency, efforts are taken to employ mobile vehicles that can sense their position and move around sensor nodes, regularly broadcasting beacons with their position. The sensor node can hear this information and estimate its position. Sichitiu and Ramadurai[5] proposed a positioning technique based on the perception of its position by a single mobile beacon. Sensor nodes estimate the RSSI values of the received messages to determine their distance to the mobile node. Finally, nodes use probabilistic methods to maintain their position estimations. In recent years, UAVs have been widely used because they are flexible and can cover the whole area. With the rapid development of UAV, more and more work is being done to locate unknown equipment [6] and [7] using UAV. Villas et al. [6], for example, used GPS-equipped drones to broadcast their geographical location when flying over the monitored area. Using these 3-D topographic maps and corresponding RSSI values, the sensor node can calculate its 3D position. Yu et al. [7] used UAV to derive the physical topology of the cloud in their cloud-coordinated physical topology discovery scheme of large-scale IoT system, to effectively detect events in real-time. It should be noted that the UAV aided positioning technology requires an accurate range estimation method and precise mobile unit position, which is difficult to obtain in practice. However, most of these techniques are discussed under relatively simple models, such as Free Space or Dual-ray Ground. To overcome these limitations, we trained our model under terrain models using Random Forests to ensure the accuracy of distance estimates.

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2.2. Localization Estimation Algorithms

The sensor node estimates the distance to the anchor node according to the RSSI value measured. With the reference position and the estimated distance, the sensor node can locate itself by using localization algorithms such as multilateration [6]. The author constructs a system of equations (at least four equations) from the target nodes and their respective distances. After linearization, the system can be solved by linear equations. Also, Savvides et al. proposed a simpler method as part of the N-hop multiple extraction algorithm. The advantage of the Min-Max method is that it only requires low computational complexity and comparison operations. Compared with multilateration and Min-Max localization algorithms, multidimensional scaling analysis (MDS) is a more popular localization method. Chen et al. [8] proved the feasibility of the classical MDS algorithm for mobile positioning, and further proposed the unified framework of the classical MDS algorithm, the improved MDS algorithm, the subspace method, and the corresponding three weighted MDS algorithms. Meanwhile, according to Kim et al.[9], a mobile Beacon-based localization is proposed using the classical multidimensional scaling (MBL-MDS), which contains selection rules to select sufficient reference positions in all received decision rules to determine the location of the two candidates on the correct node if the given reference position is placed on the same plane to improve positioning performance. To reduce the complexity of the proposed technology, some studies [10], [11] have explored the use of neural network implementation in WSNs.Specifically, some attempts have been made to integrate a single hidden layer feed-forward neural network (SLFN) systems into node positioning to make SLFN simpler than deep learning. For example, Ginanjar et al. [12] proposed a real-time node location method of UAV based on SLFN.In this paper, the positioning area is divided into several blocks of the same size. Two drones broadcast their beacon signals in each block through this small area. The system USES SLFN learning algorithm, namely extreme Learning Machine (ELM), to predict the position of each node according to the RSSI value of two UAVs. However, this method can only estimate the location of sensor nodes in a 2-D space scene. Based on the terrain model and SLFN system, a UAV assisted 3-D positioning technology is proposed. This method first USES the random forest algorithm to train the distance estimation model. The distance matrix between UAV and sensor node is obtained by RSSI. Then the feedforward network is used to estimate the location of sensor nodes.

3. SYSTEM MODEL

Deployment Of UAV and Sensor Nodes:

Randomly generate a series of positions within a designated square area. Generate the positions at which the UAVs send their signal.

Distance Estimation:

Calculate the path loss of the signal between each sensor node and the UAV by the Longley-rice terrain model. Train a random forest machine learning model to estimate the distance based on each of the RSS values.

Estimate the position of each sensor node:

Use the data set which includes both the estimated distance between every transceiver and the broadcast location of that UAV. Implement selected machine learning algorithms and certain non-machine learning algorithms for the position estimation based on the data gathered at the last step. Analyze the performance of the implemented algorithms by certain merits such as mean localization Error and percentage of sensor nodes with the reliably estimated position.

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3.1. UAV Deployment

Two UAVs traveling perpendicular to one another broadcasting their locations between certain time intervals.

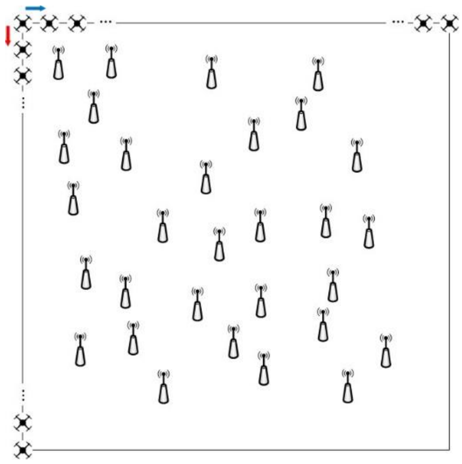

Figure 1. Deployment Of UAV

3.2. Distance Estimation

I. Feed the Random Forest model with pairs of RSS values and the corresponding distance.

II. Use the model to estimate the distance between each UAV and sensor node.

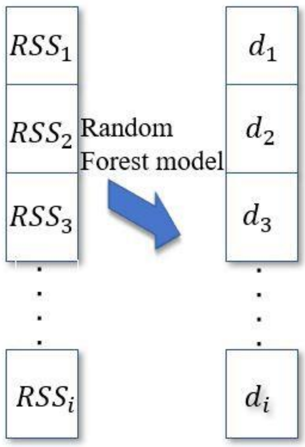

Figure 2. Random Forest For Distance Estimation

3.3. Position Estimation-Multilateration

I. Theoretically, the position of a sensor node can be calculated using a multilateration algorithm with at least 4 reference points.

II. In the scenario of non-ideal distance estimation, the least square method could be employed to calculate the position using more than 4 points.

$$(\boldsymbol{x_1} - \boldsymbol{x})^2 + (\boldsymbol{y_1} - \boldsymbol{y})^2 + (\boldsymbol{z_1} - \boldsymbol{z})^2 = \boldsymbol{d_1}^2 \tag{1}$$

$$(x_N - x)^2 + (y_N - y)^2 + (z_N - z)^2 = d_N{}^2$$

3.4. Position Estimation-MinMax

I. Use range to anchor nodes to define a bounding box.

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II. Use the center of the box as a position estimate and the aforementioned process is done by equation 2 [5].

$$[\max_i(x_i - d_i), \max_i(y_i - d_i), \max_i(z_i - d_i)] \times [\min_i(x_i + d_i), \min_i(y_i + d_i), \min_i(z_i + d_i)] \tag{2}$$

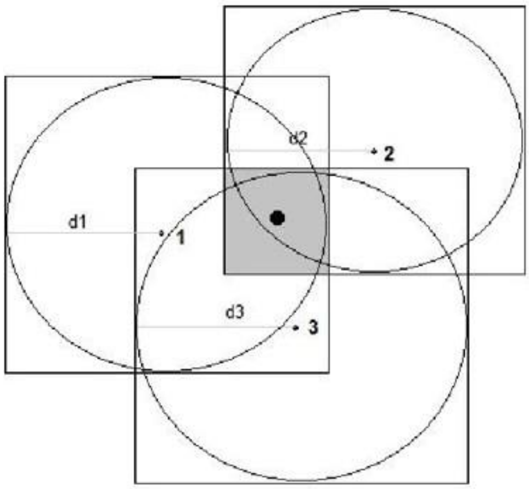

Figure 3. MinMax method

3.5. Position Estimation-Classical Multidimensional Scaling

Construct a matrix X, rows of which are the coordinates of n known points in 3-D space. Construct a squared distance matrix D as

$$\mathbf{D} = \begin{bmatrix} 0 & d_1^2 & d_2^2 & \cdots & d_M^2 \\ d_1^2 & 0 & d_{12}^2 & \cdots & d_{1M}^2 \\ d_2^2 & d_{21}^2 & 0 & \cdots & d_{2M}^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_M^2 & d_{M1}^2 & d_{M2}^2 & \cdots & 0 \end{bmatrix}_{(M+1)\times(M+1)}$$

Figure 4. Squared Matrix For MDS solving

Obtain a matrix P, rows of which are the relative coordinates of n+1 points in 3-D space using MDS as [3]. Best conform P to the known points in matrix X.

3.6. Position Estimation-Random Forest

By feeding a Random Forest Model with the same data used for multilateration, it can be trained to accurately generate the output position data when applied to the test dataset.

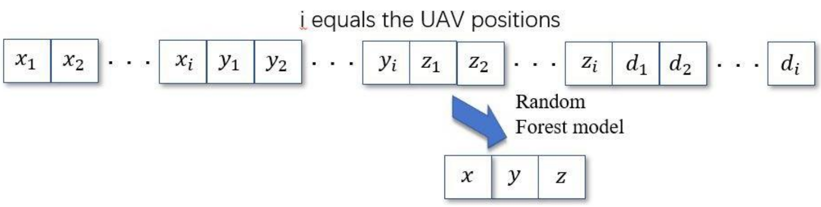

Figure 5. Random Forest For Position Estimation

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3.7. Position Estimation-Neural Network

I. The shallow network consists of only one hidden layer with 20 neurons. And is trained using the Levenberg-Marquardt algorithm (nonlinear least-square optimization), which can result in less time for convergence and better accuracy [13].

II. The trained network is then saved and used to predict the position of the test data set under different simulation settings to evaluate its performance.

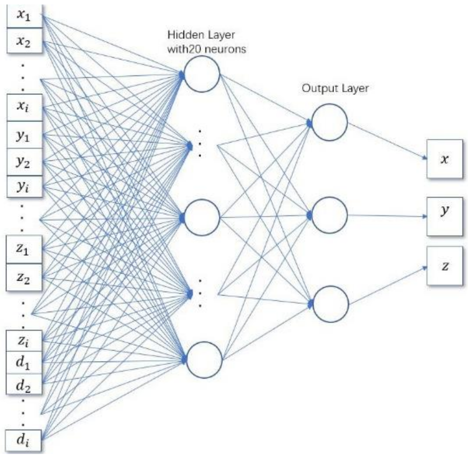

Figure 6. Neural Network For Position Estimation

3.8. Channel Model

Free space Model:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{3}$$

Two Ray Model:

$$P_r(d) = \frac{P_t G_t G_r {h_t}^2 {h_r}^2}{d^4 L} \tag{4}$$

Longley-Rice:

Calculate point to point path loss considering the effect of terrain [14].

4. PERFORMANCE ANALYSIS

4.1. Simulation Settings

We use a square area to do the simulation. Sensor nodes are randomly deployed at different height and position in this area. Then two UAVs fly at a specific altitude along the south and west side of the area respectively. The two UAVs fly at a certain speed and they broadcast their locations at a fixed time interval.

In the simulation, we will first generate a relatively denser WSN. In this step, we aim to train two sets of models: the models that use RSS values received by the sensor to predict the distance between UAVs and sensors and the models that can calculate positions from distances. For the first set, we use the simulated RSS values and the real distances between sensors and UAVs to train a random forest model to predict the distance. The RSS values are simulated by the Longley-Rice model. We also create a simple two-ray model to predict distance from RSS value, which helps us to evaluate the performance of the random forest model. Then for the second

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set of models, we generate a second random forest model and a neural network to calculate the positions of sensors. The real distances and the reallocation of sensor nodes are regarded as input and output to train the two models.

In the next step, we generate a sparser WSN in the same area for localization simulation. In this step, the UAVs broadcast their positions at a longer interval, so the total signal number that they broadcast is lesser than the former step. RSS values simulated by the Longley-Rice model are input into the trained random forest model to predict the distances. Finally, the predicted distances are input into the neural network and the second random forest model to calculate the real positions of sensor nodes. We also apply two conventional algorithms, multilateration, and MDS algorithm, to make a performance comparison and evaluate the two AI models.

Some simulation parameters are shown below:

a. The square side length is 1000 meters and the area is 1 square kilometer. The USGS GMTED2010 terrain data is used in our simulation. The coordinate of the southwest corner of the simulation area is 42.3001N, 71.3503W.

b. The altitude of UAV is 120 meters above the mean sea level. The elevation in the simulation area varies from 40m to 90m.

c. The sensor nodes are 4 meters above the ground.

d. The transmitter power is 10 Watt.

e. When we train the models, the density of WSN is 1500 nodes per square kilometer so there are 1500 nodes in total. When localization simulation, the density is 400 nodes per square kilometer and there are 400 nodes in the area.

f. When we train the models, each UAV would broadcast 668 signals during its flight. In the localization simulation, each UAV broadcasts 65 signals at the same interval during its whole flight.

g. We set the successful localization threshold of the error to be 10 meters. If the localization error is greater than this, we would regard the sensor node as an unknown node.

To observe the performance under different environments, we vary the value of some parameters.

We add uniformly distributed noise to the RSS value, then observe the result with noise from 0% to 10% of the total RSS value. We also change the number of signals that UAVs broadcast. At this time, we set the successful localization threshold to be 20 meters and change the signal number from 5 to 105, 10 for each step, to observe the localization performance.

4.2. Distance Estimation Analysis

The path loss model is 'Longley-Rice' which is described in the MATLAB function 'Propagation Model'. It calculates the point to point path loss with specific information of terrain between the transceiver [14]. To model this more realistic path loss. It can be shown in figure 7 that two ray model is less accurate than the trained random forest model using this more realistic data.

As is shown in figure 7 the error in distance estimation for the two-ray model increases substantially with the height of the sensor node above the ground increases. Although the error in distance estimation using a random forest model suffers a small number of fluctuations, its error is fixed at around 1-2 meters. Since the random forest model have less chance of overfitting if the number of observations is significantly larger than the number of predictors [15]. In this case, there is only one predictor against the size of the training data set which is 1500.

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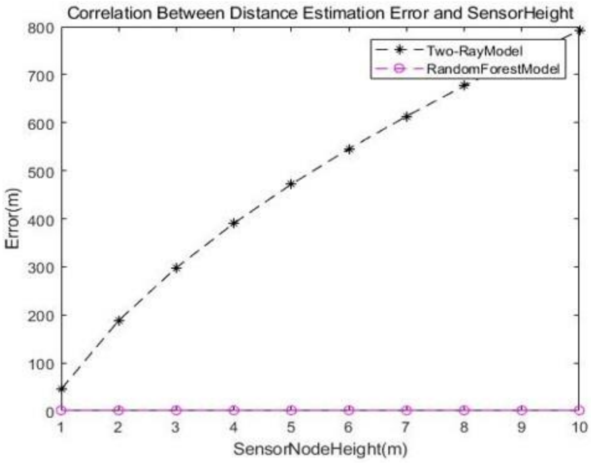

Figure 7. Comparison between Two Ray Model and Random Forest Model in distance Estimation

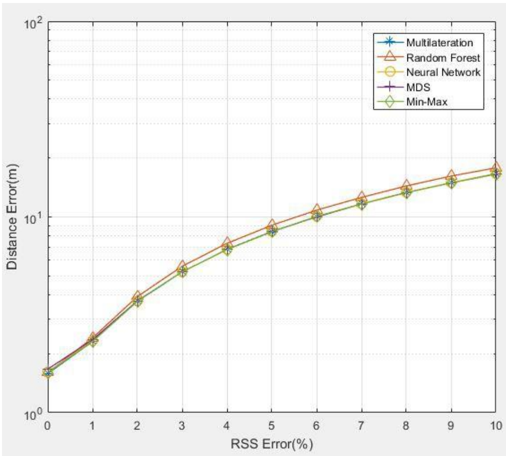

Fig 8. The mean distance estimation error later introduced to each position estimation algorithm

Figure 8 shows the mean distance estimation error for 300 sensor nodes against the uniformly distributed RSS noise. This shows that the distance estimation model is influenced by the additional noise of the RSS and causing the estimation of a deviation from the real distance.

4.3. Location Estimation Analysis

Figure 10 shows the mean and maximum localization error against the number of beacon positions used. For the MDS algorithm, a significant decrease in error is seen with an increase of anchor positions initially and the error decreases gradually while keep increasing the anchor positions. That is because the MDS algorithm requires a large size of the matrix (anchor nodes positions) to solve accurately the location of each sensor node [9]. However, to construct the matrix, a substantial amount of time is required given the size of the matrix. So for this computation to be done on the sensor node side can be challenging. The random forest model sees an increase of error with an increase of anchor positions, which can be attributed to the overfitting of training data. For in this scenario, the number of predictors parallels that of observations.

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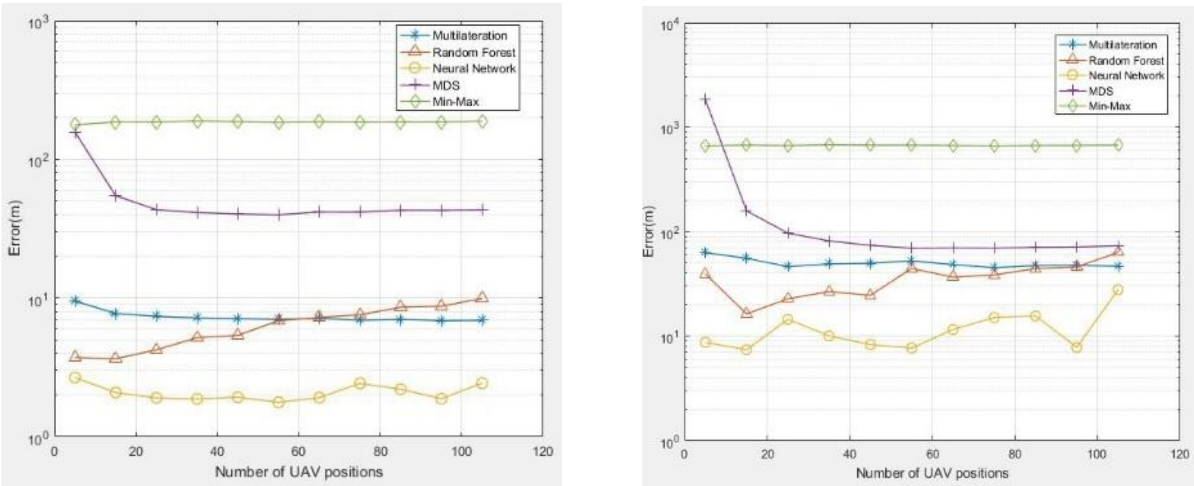
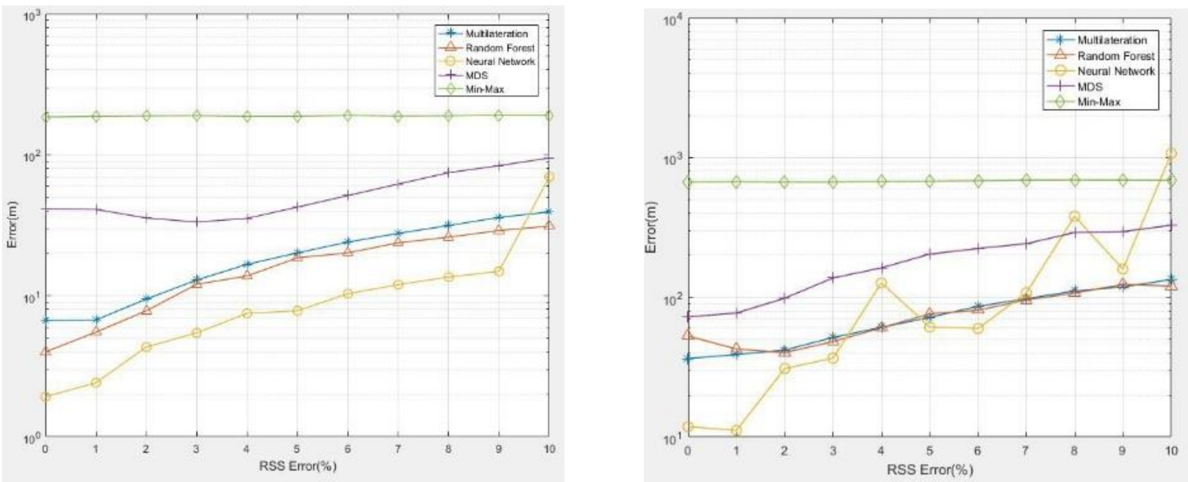


(a) (b)

Figure 9. Mean and Maximum Localization Error against the number of anchor positions. (a) Mean; (b) Maximum.



(a) (b)

Figure 10. Mean and Maximum Localization Error against RSS Error. (a) Mean; (b) Maximum.

The introduced RSS Error is a uniform distribution added on top of the RSS in watts. It corresponds to the additional noise on the received signal due to the non-ideal transmitting condition. The error of all localization algorithm increases although with different magnitude with the increase of RSS error. Among these discussed algorithms, the neural network performs the best, lower than that of multilateration and other algorithms in both the mean error and many cases of maximum error except some rogue points in figure 10 (b).

Another metric is introduced for the performance analysis of different localization algorithm. If the localization error is more than 10m, we consider it is not accurate enough to yield a valid sensor node's position. In which case the node is considered unknown.

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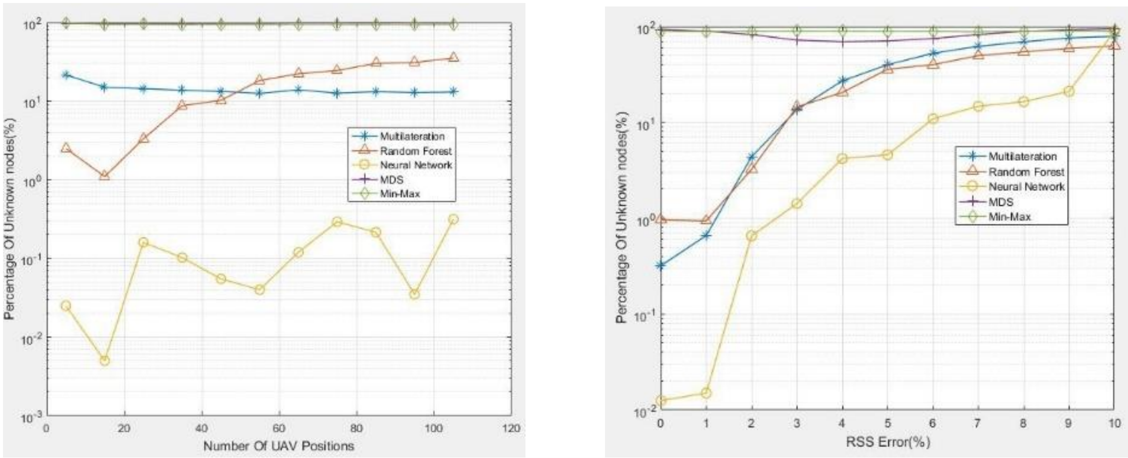

(a) (b)

Figure 11. Percentage of unknown nodes against the number of anchor positions and RSS error respectively. (a): anchor positions; (b) RSS error

Figure 11(a) plots the percentage of unknown nodes against the number of anchor positions used to calculate the position of the sensor node. The percentage of neural network algorithm remains the lowest and do not increase or decrease as the increase of anchor positions except some fluctuations which is the result of randomness. It is shown that only a small number of UAV positions are needed at the sensor node side to achieve a valid estimation of the sensor node's position. This is also the result that one hidden layer feedforward neural network with enough neurons can approximate any function with finite response [13]. Unlike that of multilateration and all other algorithms, whose error only decreases with the information of more anchor positions, which is advantageous considering in a more realistic situation where not all the sensor nodes can receive reliably the same large number of UAV positions.

Figure 11(b) plots the percentage of unknown nodes against the introduced RSS Error (uniformly distributed). In all points except one at 10 percent RSS error, the percentage of known nodes is the lowest for neural network algorithm compared with all other algorithms. This shown the robustness of neural networks even at the presence of large noise factors. Besides, the Min-Max algorithm fails under almost all conditions discussed above to accurately produce the position of the sensor node. That is due to that the algorithm requires the anchor positions to be around the sensor node at all directions to produce a reliable position estimation. Since the UAV route is set and quite simple (going straight line and two routes perpendicular to one another in Figure 1), the thus generated bounding box cannot be employed to accurately generate the position.

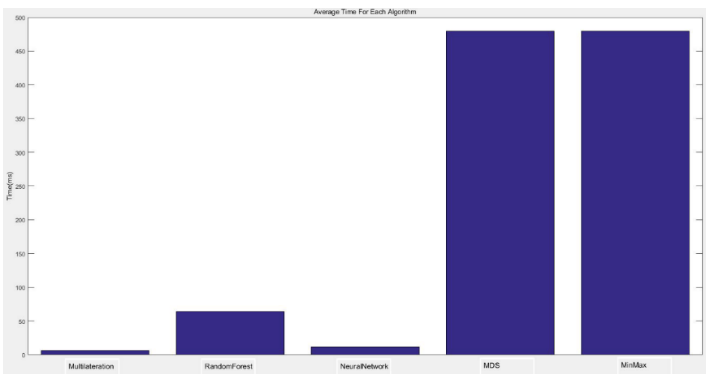

Figure 12. Average Time For Each Algorithm

As for the computational complexity, the preliminary analysis shows average computation time run in MATLAB (average 50 times) for the execution of each algorithm discussed, which is expected to be a manifestation of the computational requirement of each algorithm. As can be shown in figure 10, since the implementation of MDS and Min-Max all requires the construction of a comparatively larger matrix for solving, it takes the most amount of time and has the largest error. Meanwhile, the neural network does not need much more computational time than multilateration and yet can achieve the best result.

5. CONCLUSION

In this paper, a 3-D localization method of UAV wireless sensor network node based on a machine learning algorithm is proposed. The system USES one or more UAV as the mobile anchor, instead of the traditional ground anchor, beacon signal broadcast, easy to locate. In this way, a line-of-sight (LoS) communication link can be established between the UAV and sensor nodes during the UAV movement, while static positioning technology will encounter non-LINE-of-sight (NLoS) problems, such as obstacles. Therefore, the technique is suitable for situations where ground anchors cannot be deployed in an optimal position.

This method can be used to calculate the position of the sensor based on the beacon signals received from the mobile UAV with estimated efficiency and accuracy. Neural networks trained by using several machine learning algorithms will be compared with other proposed systems. You can also choose the best algorithm for computer research.

The analysis of the relevant parameters of the neural network structure and the analysis of the performance of multiple UAVs to improve the positioning accuracy and coverage may be explored in our further research.

In the current simulation, the route of the UAV is set, resulting in possibly low signal strength of the sensor node from a large distance and render certain algorithms such as Min-Max ineffective. As a result, more complex and novel UAV routes should be discussed and its impact on the Localization accuracy. And also in this simulation, we assume all sensor nodes are within UAV's communication range at all UAV positions. Communication Range could also be set for more realistic conditions. Also, the machine learning model for distance estimation is trained using terrain at a certain area, more terrain areas could also be employed to train a Random Forest model to improve its generality which has the potential to be universal under all types of terrains.

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