**An Efficient 3-Dimensional Node localization Using Recurrent Neural Networks in Unmanned Aerial Vehicle Assisted Wireless Networks**

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**Abstract:**

Accurate localization of nodes is crucial for numerous applications, including environmental monitoring, disaster management, and asset tracking. Unmanned aerial vehicle (UAV) assisted node localization is a novel approach to accurately and efficiently localize nodes in wireless sensor networks (WSNs) because UAVs communicated the unknown nodes through reliable air-to-ground communication link. The classical received signal strength (RSS)-based localization techniques rely on measuring the signal strength of wireless signals, which can be highly affected by environmental factors such as obstacles, multipath interference, and signal attenuation. Neural network (NN)-based approaches, on the other hand, can learn complex patterns and relationships in the received signals, allowing them to handle variations more effectively and provide more robust localization results. In the family of NNs, the multilayer perceptron (MLP) and recurrent neural network (RNN) models are popular due to their versatility and effectiveness in various applications. Further, the RNN has an edge over MLP as it also considers previous network output for network training. We evaluate the performance of our method through extensive simulations. The results demonstrate that the UAV-assisted node localization using NNs achieves superior localization accuracy compared to existing methods.

**Keywords:** Unmanned Aerial Vehicles, Multilayer perceptron, recurrent neural network, received signal strength. Wireless sensor network.

1. **Introduction**

Wireless sensor networks (WSNs) have attracted a lot of attention recently, due to their numerous uses [1]. Accurate node localization in WSNs is crucial for tasks such as target tracking, event detection, and data fusion. Traditional localization methods often rely on range-based or connectivity-based techniques, which can be challenging to implement, especially in large-scale networks [2]. To address these challenges, researchers have explored the use of unmanned aerial vehicles (UAVs) to assist in node localization. This literature review provides an overview of the existing research in UAV-assisted node localization using neural networks [3-5]. UAV-assisted localization techniques have emerged as a promising solution to enhance the accuracy and scalability of node localization in WSNs. These techniques leverage the mobility and aerial perspective provided by UAVs to capture visual information from different angles. The captured images are then processed using neural network models to estimate the positions of the nodes. Various approaches have been proposed in the literature to achieve UAV-assisted node localization.

The study in [6] presents a comprehensive survey on the utilization of unmanned aerial vehicles (UAVs) in WSNs. The focus of this survey is strongly on UAVs for data collection in WSNs. This paper discusses various techniques such as communication links, control algorithms, network structures, and mechanisms to support UAVs in WSNs, considering factors like energy consumption and transportation costs. One approach is to use traditional computer vision algorithms combined with UAV imagery. For instance, Li et al. [7] proposed a method that extracts features from UAV images using SIFT (Scale-Invariant Feature Transform) and performs node localization using an extended Kalman filter. Although effective, these methods heavily rely on handcrafted features and may not capture complex spatial relationships accurately. In another study, Al-Fuqaha et al. (2018) proposed a UAV-assisted localization system that utilized a hybrid approach of range-based and image-based localization [8]. The system employed a UAV equipped with both a camera and range sensors to collect data from the sensor nodes. The data was then processed using a combination of neural networks and range-based algorithms to estimate the node positions. This work presented in [9] addresses the challenge of finding and querying smart sensor nodes in industrial UAVs using a combination of Ultra-Wideband (UWB) and Wake-Up Radio (WUR) communication technologies. The UAV performs localization of the sensor nodes through UWB range measurements and then performs energy-efficient data acquisition in their proximity. In another study, Wang et al. (2020) introduced a novel approach that combined UAV imagery and received signal strength (RSS) measurements for localization in large-scale WSNs [10]. They utilized a graph-based algorithm to estimate the positions of the sensor nodes based on UAV-captured images and RSS information. Furthermore, Yang et al. (2021) presented a comprehensive survey on UAV-assisted localization techniques in WSNs, highlighting different localization approaches, communication protocols, and energy-efficient mechanisms [11]. The survey discussed the challenges and opportunities in utilizing UAVs for node localization, providing insights into the advancements in this field.

In recent years, deep learning techniques, particularly NNs, have shown remarkable performance in computer vision tasks. Researchers have leveraged the power of neural networks to develop image-based node localization methods. For example, the study in [12] proposed convolutional neural network (CNN) architecture to estimate node positions using UAV images. The network learned to extract discriminative features and achieved higher accuracy compared to traditional methods. Several studies have explored different aspects of UAV-assisted node localization. For instance, Li et al. (2019) proposed a localization approach using UAV-mounted cameras and deep learning techniques for accurate node localization in outdoor WSNs [13]. They achieved improved localization accuracy by leveraging visual information captured by the UAV. In a more recent study, Wang et al. (2021) proposed a UAV-assisted localization method that utilized a graph neural network (GNN) to estimate the node positions [14]. The method employed a UAV equipped with a camera and flew over the sensor network area, capturing images of the nodes from different angles. The images were then processed using the GNN to learn the spatial relationships between the nodes and estimate their positions. To address the nonlinear distortion isuue, the study in [15] proposes the use of a MLP as a robust tool for node localization in UAV-aided WSNs. MLPs can handle complex nonlinear mappings between input (e.g., signal measurements) and output (e.g., node locations) data, resulting in improved localization accuracy and reduced deployment costs. In summary, UAV-assisted node localization using NNs has shown promising results in improving the accuracy and efficiency of node localization in WSNs. The proposed methods have utilized various deep learning techniques, including convolutional neural networks and graph neural networks, to capture complex spatial relationships between the sensor nodes. The use of UAVs for data collection has also provided advantages in coverage, scalability, and efficiency compared to traditional methods. On the other hand, RNNs are a type of NN that can effectively model sequential data by capturing temporal dependencies and contextual information [16]. They are well-suited for processing time series data, making them a natural choice for handling the dynamic and time-varying nature of node localization in WSNs. By leveraging the capabilities of RNNs, UAVs can intelligently analyse sensor data over time, improving the accuracy and reliability of node localization. The combination of UAVs and RNNs in node localization brings several advantages. Firstly, the mobility of UAVs allows for flexible positioning and collection of sensor data from multiple locations, enabling comprehensive coverage of the sensing area. Secondly, RNNs can capture long-term dependencies and patterns in the collected data, facilitating more accurate localization results. This is particularly beneficial in scenarios where nodes may undergo changes in their positions or exhibit complex movement patterns. In this paper, we propose a UAV-assisted node localization framework utilizing RNNs. We investigate the use of RNN architectures to effectively model the temporal dynamics of sensor data and predict node locations. We will also present experimental results and performance evaluations to demonstrate the effectiveness and accuracy of our approach compared to existing localization methods.

The remainder of the paper is organized as follows. Section 2 provides a comprehensive system model of related works in the field of node localization and UAV-assisted localization techniques. The MLP model for node localization is discussed in Section 3. Section 4 presents the methodology and design of proposed UAV-assisted node localization system using RNN. Section 5 describes the experimental setup and presents the results and analysis. The paper is concluded with a summary of the results in Section 6.

1. **System model**

Consider a three-dimensional (3D) dimensional sensor field as shown in Figure 1, where each of the *P* number of Unmanned Aerial Vehicles (UAVs) carries an Anchor Node (AN). These UAVs with ANs are denoted as AUs. The UAVs are assumed to fly between *h*min to *h*max. These UAVs are used to localize randomly distributed *Q* number of 3D Target Nodes (TNs) in a given area of interest. To transmit signals to UAVs, we assume that the TNs are equipped with id-linked radio transmitters, such as Bluetooth, Wi-Fi, or ultra-wideband (UWB) tags. These UAVs can also be equipped with RF sensors to record strength of the RF signal received from each TN. The communication technology between AUs and TNs could be LTE or WiFi, or as simple as LPWAN [17]. The received signal strengths (RSSs) are used to compute distances between AUs and TNs [18]. Later, these distances are converted to coordinates of TNs using multilateration proves. The multilateration requires at least four UAVs to compute the coordinates.



**Figure 1: Localization of *Q* target modes using *P* UAVs.**



**Figure 2: Localization of *q*th target node using *P* AUs**

The schematic diagram for localizing *q*th TN using *P* UAVs is depicted in Figure 2, where *p*th UAV flies at an altitude of *hp* and *P* should be at least four. As illustrated in this figure, *dpq* and *gpq* refer the direct and ground distances between *p*th AU and *q*th TN, where ground distance refers to the distance between TN and the perpendicular projection of UAV on the place of TN’s existence. Let the 3D co-ordinate projection of *p*th AU on the plane of TN be (*ip*, *jp*, *kp*) and (*xq*, *yq*, *zq*) is the 3D co-ordinate of *p*th the *q*th TN, where *zq* is the altitude of TN from the ground field and it becomes zero if TN is located on ground field. The log normal shadowing model (LNSM) is used to estimate the distances between AUs and the TN. Thus, the RSS measured in dBm at *p*th AU while receiving signal from *q*th TN is given by:

 (1)

where *P*0 is the RSS measured at reference distance *d*0, *dpq* is the true distance between *qth* TN and *p*th AU, *γ* is path loss exponent, and *χσ* is the parameter that represents log-normal shadowing effects. So, *χσ* is the Gaussian distributed i.i.d random variable with zero mean and *σ*2 variance. Thus, the distance between *qth* TN and *p*th AU using the RSS measurement given in eq. (1) is estimated as:

 (2)

From the estimated direct distances, the square ground distances can be computed as:. Let be the estimated position of *q*th TN, then the set of square distances from *N* AUs to *q*th TN is mathematically written using multilateration as:

 (3)

For simplicity, the set of equation given in eq. (3) can be written as a set of linear equations in terms of,  and. To accomplish this, remove the most recent equation from all earlier ones. Thus, eq. (3) can be modified as:

 (4)

The eq. (4) can be written in matrix form as:

*U×Lq* = *V* (5)

where,is the position of *q*th TN,

and

Then, the location of *q*th TN can be obtained from:

 (6)

1. **3D node localization using MLP model**

RSS-based techniques rely on measuring the RSS of wireless signals transmitted by ANs. Based on LNSM, the RSS is used to calculate the separation between the target node and the anchor nodes. RSS-based techniques can achieve reasonable accuracy depending on factors like the quality of signal measurements, propagation models used, and calibration accuracy. However, they may suffer from limitations due to environmental factors, multipath effects, and signal interference. NN-based techniques, on the other hand, utilize ANNs to learn the mapping between RSS values and node positions. They leverage the power of machine learning to establish a relationship between signal measurements and node localization. Neural network-based techniques can potentially provide higher accuracy and precision compared to RSS-based techniques. By leveraging the learning capabilities of neural networks, they can capture complex relationships between signal measurements and node positions, leading to improved localization performance.



**Figure 3: Architecture of MLP model for localizing *q*th TN**

A popular type of NN in machine learning and deep learning is the multilayer perceptron (MLP) [19]. It is a feedforward neural network, which means that data moves without loops or feedback connections in a single direction, from the input layer to the output layer. The MLP is made up of numerous layers of artificial neurons or interconnected nodes. While the neurons in the output layer correspond to the expected outcomes, each neuron in the input layer represents an input feature. Hidden layers are those layers that exist between the input and output layers. The BP technique, which is widely utilized, can be effectively used to train the MLP weights [20]. Two essential procedures are involved in training an MLP: backpropagation and forward propagation. The anticipated outputs are computed when the input data is fed through the network during forward propagation. The calculated inaccuracy is then calculated by comparing the calculated outputs to the desired outputs. In order to reduce the discrepancy between expected and desired outputs, BP is used to adjust the weights of the links in the network based on the computed error. Up till the network achieves a suitable degree of accuracy, this iterative procedure is continued. MLPs have a number of benefits. They are suitable for a variety of tasks, including classification, regression, and pattern recognition, due to their ability to learn and represent complicated patterns in data. Given enough hidden units and the right activation functions, they can also approximate any non-linear function. MLPs can be used for both supervised and unsupervised learning and can handle both continuous and categorical input data. As a result, TN positions in a WSN are likewise estimated using the MLP model [16].

Figure 3 depicts the MLP architecture while employing *P* AUs to localize the *q*th TN. Figure 4 depicts the MLP model used for localizing the UN in the UAV-assisted WSN. This picture depicts the MLP model, which has *P* input elements, *H* hidden neurons, and a three-neuron output layer. The three output neurons calculated the *q*th TN's *x*, *y*, and *z* coordinates. The related weights in an MLP that govern the strength of the connections between neurons. Each neuron processes the weighted total of its inputs through an activation function to create an output, which is then transmitted to the following layer. The network gains non-linearity from the activation function, which enables it to recognize intricate patterns and generate non-linear predictions. As a result, each hidden neuron's output is expressed as follows:

 (7)

where, *αhp* denotes connection weight between the *h*th hidden node and *p*th input node. The sigmoid function is used as the nonlinear activation function *ψ*(.), that is *ψ* (*t*) = 1/(1 + *e*–*t* ). The three two output neurons consist simple summers. So, the estimated *x*, *y* and *z* coordinate of *q*th TN are obtained from the three output neurons as:

 (8)

 (9)

 (10)

where, *V*1*h*, *V*2*h* and *V*3*h* respectively are the connection weights between first, second and third output nodes and *h*th hidden node.

1. **3D node localization using proposed RNN model**

The MLPs also have some limitations. To generalize successfully and avoid overfitting, they need a lot of labeled training data. They can be sensitive to the initial weights and architecture choices, making them prone to getting stuck in local optima. Training large MLPs can be computationally expensive, especially when dealing with high-dimensional data. To address some of these limitations, variations of MLPs have been developed, such as RNNs for sequential data. These variations leverage specific properties of the data to improve performance and efficiency. RNNs are more suited for tasks involving sequential or time-dependent data because they feature feedback connections, which, in contrast to feedforward neural networks, allow information to remain over time steps. The ability of an RNN to preserve an internal state, or memory, that records data from earlier inputs, is its important feature [21]. This memory is passed along with the current input to produce an output and update the state for the next time step. This recurrent nature allows RNNs to capture temporal dependencies and context in the data. Because of its built-in self-feedback structure, the RNN model might outperform the MLP model. Also, since it avoids using hidden layer, its complexity is also smaller than the MLP network. Training an RNN involves a process called real time recurrent learning (RTRL) [22]. It is similar to backpropagation in feedforward neural networks but takes into account the sequential nature of the data. RTRL propagates the error from the output back through each time step, allowing the network to learn from its past mistakes and adjust its weights accordingly. Thus, RNN is considered to be an efficient for node localization in WSNs.



**Figure 4: Architecture of RNN model for localizing *q*th TN**

The architecture of RNN model used for localizing *q*th TN is depicted in Figure 4. The RNN model shown in this figure has an input layer of *P* + 3 elements. Out of these *P* + 3 elements, *P* elements contains planar distances of *q*th TN from *P* AUs and 3 elements contains estimated *x*, *y*, and *z* position of the *q*th TN in the previous iteration that are feedback from output layer. The output layer consists of threeneurons and these neurons estimates *x*, *y*, and *z* position of the *q*th TN. the external input vector and one time instant delayed output vectorwith zero initial state are combined to form an input vector ***a***. Hence, the *k*th element of the input vector is given by:

 (11)

Each output neuron consists of a summer and a non–linear activation. Hence, the estimated *x*, *y* and *z* coordinate of *q*th TN are obtained from the three output neurons as:

 (12)

 (13)

 (14)

where, *w*1*k*, *w*2*k* and *w*3*k* respectively are the connection weights between first, second and third output nodes and *k*th input element. The activation function *ψ*(.) is the same sigmoid activation function that we used for MLP.

1. **Simulation analysis**

**Table 1: Simulation parameters**

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| Sensor field dimension | (100×100×35) *meters* |
| Number of AUs (*P*) | 4 |
| Number of TNs (*Q*) | 25 |
| Height of the UAV (*hp*) | 40 *meters* |
| Height of the TNs (*hq*) | (0-35) *meters* |
| Path-loss constant (*γ*) | 3.1058 |
| Standard deviation (*σ*) | 2.8189 |
| Reference distance (*d0*) | 1 *meter* |
| Transmitted power at reference distance (P(*d0*)) | -27.143 dB |
| Number of output nodes of MLP and RNN | 3 |
| Number of input nodes of MLP (*P*) | 4 |
| Number of input nodes of RNN (*P+*3) | 7 |
| Number of hidden neurons of the MLP (*HN*) | 8 |
| Learning rate of MLP and RNN | 0.08 |

In this section, the efficacy of the proposed RNN based node localization is tested and compared with MLP and RSSI based node localization through simulation analysis. In these simulations, we have assumed at least four UAVs are used to localize each TN. The Monto-Carlo simulations are performed by averaging 100 times to locate each TN to obtain true locations. The rest of the simulation parameters are highlighted in Table 1 [23]. The accuracy of the localization techniques is evaluated with respect to average localization error (AvgLE), which is expressed as follows:

 (15)

Figure 5 shows actual position and estimated position of the *q*th TN using RSS with the help of four AUs. The four AUs are located at a height of 40 meters from the ground. The RSS based localization with increased number of AUs is depicted in Figure 6. The estimated and actual positions of *Q* number of TNs are shown in Figure 6(a), Figure 6(b) and Figure 6(c) respectively when the number of AUs is 4, 5 and 6. As shown in this figure, the actual and estimated positions are approaching closer as we increase number of AU. By increasing the number of anchor nodes, you are essentially increasing the amount of information available for the localization algorithm to compute the position of the target node. With more anchor nodes, the algorithm can incorporate additional measurements and use triangulation or trilateration techniques to estimate the target node's position more accurately. So, the localization error minimizes with more number of AUs as shown in Table 2.



**Figure 5: Localization of *q*th TN using four AUs.**



**(a)**



**(b)**



**(c)**

**Figure 6: RSS based localization of *Q* TNs with *P* AUs (a) *P* = 4 (b) *P* = 5 (c) *P* = 6**

The actual and estimated positions of *Q* TNs with four AUs using RSS, MLP and the proposed RNN based localization is illustrated respectively in Figure 7(a), Figure 7(b) and Figure 7(c). RSS-based techniques can achieve reasonable accuracy depending on factors like the quality of signal measurements, propagation models used, and calibration accuracy. However, they may suffer from limitations due to environmental factors, multipath effects, and signal interference. By contrast, NN-based techniques can potentially provide higher accuracy and precision compared to RSS-based techniques. By leveraging the learning capabilities of neural networks, they can capture complex relationships between signal measurements and node positions, leading to improved localization performance as shown in Figure 7(b) and Figure 7(c), where the actual estimated positions are almost coincides. Further the RNN based localization has an edge over MLP based localization because the RNN also considers the previous outputs while training the network. This may lead further lower AvgLE over ML as presented in Table 3.

**Table 2: ALE of RSS algorithm with increased number of AUs**

|  |  |
| --- | --- |
| ***P*** | **AvgLE (in *meters*)** |
| 4 | 4.1273 |
| 5 | 3.2424 |
| 6 | 2.8573 |

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**(a)**

****

**(b)**

****

**(c)**

**Figure 7: Localization of *Q* TNs with four AUs using (a) RSS (b) MLP (c) RNN**

**Table 3: ALE of RSS algorithm with increased number of AUs**

|  |  |
| --- | --- |
| **Technique** | **AvgLE (in *meters*)** |
| RSS | 4.1273 |
| MLP | 1.1035 |
| RNN | 0.8462 |

Localization errors obtained for each TN with RSS, MLP and RNN techniques are shown in Figure 8(a), Figure 8(b) and Figure 8(c) respectively. The choice of localization algorithm and techniques used in the system can influence the localization error of individual nodes. Different algorithms may have varying levels of accuracy and robustness, and certain algorithms may perform better in specific scenarios. The variance in the localization errors while using RSS technique is more as we see in Figure 8(a), whereas the variance of localization errors while using MLP and RNN techniques is less due to their inherent capabilities. Thus, NN-based techniques try to localize all nodes with nearly equal precision compare to RSS technique as we see in Figure 8(b) and Figure 8(c).

 

**(a) (b)**



**(c)**

**Figure 8: Localization error computed for each TN while using: (a) RSS (b) MLP (c) RNN**

1. **Conclusion**

In this paper, we have explored the concept of UAV-assisted node localization using neural networks in wireless sensor networks (WSNs). The integration of UAVs and NN techniques offers a promising approach to address the challenges of accurate and efficient node localization. The UAV-assisted node localization has several advantages for WSNs. It eliminates the need for manual calibration and configuration of sensor nodes, simplifying the deployment process. The aerial perspective of UAVs enables simultaneous localization of multiple nodes and coverage of larger areas, enhancing scalability and efficiency. Traditional localization technique in WSNs such as RSS often require manual configuration and suffer from limitations in accuracy, scalability, and efficiency. However, the utilization of NNs, particularly MLP and RNN, allows for capturing complex spatial relationships and patterns, leading to improved localization accuracy. Further, the RNN technique even performs better than MLP because RNN has a recurrent connection that allows it to maintain an internal memory or hidden states.

Thus, UAV-assisted node localization using neural networks presents a promising approach to overcome the limitations of traditional localization techniques in WSNs. The combination of UAVs, cameras, and deep learning algorithms offers improved accuracy, scalability, and efficiency in node localization. This paper opens up new possibilities for enhancing the capabilities of WSNs and enables a wide range of applications that rely on precise node localization.

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