SimNet:UAV-Integrated Sensor Nodes Localization for Communication Intelligence in 6G Networks

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***Abstract*—Achieving communication intelligence with a low computational cost is necessary for wireless sensor networks for the drone transportation system. This work proposed a novel localization system with low computational and time efficiency that uses an unmanned aerial vehicle (UAV) as anchor node and lightweight neural networks to evaluate the UAV position information. The scheme takes advantage of the capabilities of artificial intelligence models. Simulation results indicate that the proposed scheme displayed a good performance with the least localization error of 1.75, least training time of $0.0032s$, and testing time of $0.00039s$ without requiring GPS when compared to other algorithms and previous schemes.**

***Index Terms*—communication intelligence, drone transportation, edge network, 6G, UAV, wireless sensor networks**

I. Introduction

THE critical application of communication intelligence (CI) for self-sustaining networks (SSN) in 6G requires high-reliable, low latency, security-driven, and scalable artificial intelligence (AI) algorithms, with reliable network infrastructure that integrates unmanned aerial vehicle (UAV)-ground network nodes. Without this in place, the acceleration of the use of drones to transport goods and services, otherwise called a drone transport system (DTS), will be jeopardized [1]. Deep learning (DL) algorithms enable devices connected to wireless communication systems (WSNs) to dynamically and intuitively monitor their environment by exploiting multifaceted data features to learn, predict, and adapt to environmental stimuli such as wireless channel dynamics and mobility patterns, traffic, network composition, etc.

WSN also called edge network (EN) is an interconnection of sensor nodes to track distinct conditions in a particular space/surrounding. Each node has low-complexity computation units that enable it to carry out simple repetitive tasks like collecting data from its immediate environment and disseminating it through a wireless channel to its destination. As a distributed information technology model, edge networks allow client data to be processed at the boundary of the network, close to its source. Hence, each sensor node can communicate its information with other nodes in the same network to expand the scope of the coverage area being monitored and/or boost the decision-making capability of the edge network as shown in Fig. 1. Therefore, the decision is to establish the best action to react to when certain events occur in the network. To achieve this, useful meaning needs to be extracted from the information sent by the nodes and the transmitter with the help of a knowledge base. This is the main objective of semantic communication [2].

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To localize the position of a node in a communication network, the most adopted solution is the global positioning system (GPS). However, utilizing GPS increases the deployment cost of communication nodes and is unsuitable for several applications. Hence, to replace GPS usage for all the sensor nodes in the network, a localization algorithm for WSN and/or EN is prime in reducing communication node deployment costs. With semantic communication and intelligent connected unmanned aerial vehicles (IC-UAVs), computational costs can be drastically minimized.

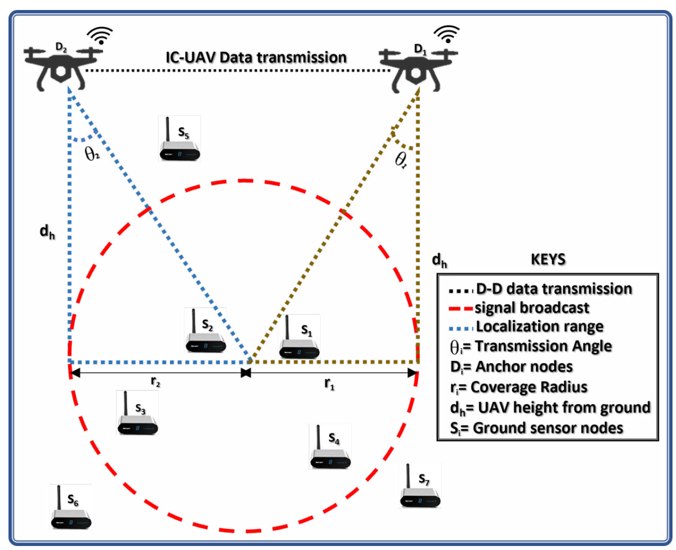

Fig. 1. Communication between UAV and Ground sensor nodes

Therefore, the integration of unmanned aerial vehicles (UAV) into EN technology can improve the performance of communication protocols, since the mobility of UAVs in the airspace easily establishes connections with neighboring nodes in the same network shown in Fig. 1. Previous research on UAV-based sensor node localization systems was proposed by authors [3]–[6]. These approaches used deep learning neural networks

(DL). However, the application of DL-based approaches on UAVs for on-the-fly deployment and decision making is usually restricted by its limited power sources, battery capacity, and on-board processing capabilities. Therefore, the continuous reinvention of computationally efficient, communication intelligent, and hardware deployable DL solutions for UAVs is due to its enormous benefits for dynamic aerial communication in the 5G and 6G networks [7].

In this paper, a novel Simple Integrated Multi-layer Neural Network (SimNet) for edge networks with minimal computational complexity and a time-efficient node localization system is proposed based on feed-forward shallow neural network architecture. By deploying UAVs as anchor nodes, high-quality beacon signals can be transmitted freely and processed by unknown nodes without undue interference from ground obstacles as the UAVs can move freely in the airspace with a low-computational resource.

Therefore, this study was designed to achieve the specific objective of developing a time-efficient sensor node localization scheme with minimal resource usage for intelligent connectivity leveraging the flexibility of UAVs and the capabilities of artificial intelligence. This paper is organized as follows. Section II for Problem formulation; Section III highlights the results and performance evaluation; and Section IV concludes the paper.

II. Problem Formulation

The localization scheme as seen in Fig. 1 divides the deployment of UAV into smaller blocks. D_1 and D_2 UAVs serve as anchor nodes for broadcasting beacon signals to neighboring nodes. However, the UAVs can only provide information to sensor nodes within its transmission range; S_1, $S_2,: S_3$, S_4 or coverage radius, r_i. The value of r_i depends on the transmission angle of the UAV's antenna, θ_i, and the height of the UAV, d_h. Thus, D_1 and D_2 can only transmit beacon signals to 4 sensor nodes at a time, but with a change in movement, it can cover the other 3 nodes; S_5, S_6, and S_7. Specific sensor nodes S_1, S_2 within r at a time t are considered connected states that serve as input characteristics for training the neural network. We assumed that the deployed UAV has two antennae (left and right) to send two signals simultaneously to the sensor nodes in the localization block that is denoted b_1, b_2, ...to b_{n-1}.

A. Data Preprocessing

The distinct position of a sensor node is derived from the left (R^-) and right (R^+) antenna's received signal strength indicator (RSSI) values which contain the signal properties of the connected beacon signals from the anchor node. These values, R_i^- and R_i^+ for maximum connected states are stored in a repository and subsequently fed into the proposed neural network. To extract relevant features from the saved data; maximum RSSI (R_M), number of connected states (n_t), mean (μ) and the standard deviation (σ) are used.

To derive R_M value; it is the highest value of RSSI R_i from a series of specific R_i^- and R_i^+ values expressed as:

$$\Rightarrow R_M = max(R_i), \tag{1}$$

where R_i is the matrix of observed RSSI values.

The mean, μ is a statistical tool that measures the central tendency of a given distribution. It is defined by the average number of the features extracted from the saved data. It is computed as;

$$\Rightarrow Mean(\mu) = \frac{\sum_{i=0}^{n_t-1}(R_i)}{n_t}, \tag{2}$$

where n_t = total number of connection states.

σ is a measure of the variability or dispersion of a given set of values mathematically expressed as:

$$\Rightarrow Standard\, deviation(\sigma) = \sqrt{\frac{\sum_{i=0}^{n_t-1}(R_i - \mu)}{n_t-1}}. \tag{3}$$

A low σ value indicates that the set of values is close to the expected value μ. Finally, the number of connected states, n_t is the last data feature that represents the established connection between the sensor node and the anchor node (UAV). The rule is; that given that the n_t value for R_i^- is different from R_i^+, the greater value is chosen as the data feature. With this process, a matrix of extracted data features is generated for the training of neural networks. In all, there are seven features comprising three μ, R_M, and σ for the right and left antennas. This forms the total sample size for several generated values for model training and testing.

B. Proposed SimNet Architecture

SimNet architecture is a simple neural network with a single hidden layer, as seen in Fig. 2.

Unlike previous DL-UAV localization approaches, SimNet adopts the shallow learning technique. Mathematically, it is summarized as;

$$\begin{gathered}\sum_{i=1}^{n_t} \psi_i' . \eta(\omega_i \times x_j + b_i) = z_j, \\ j = 1, ..., n_t,\end{gathered} \tag{4}$$

where n_t = total training samples; ψ_i' = output weights vector connecting hidden layer to the output layer; $\eta(\bullet)$ = the hidden nodes activation function; ω_i = weights of vector connecting input and the hidden layer; b_i = hidden nodes bias value, z_j = output layer of the network. Two indexes, i and j representing specific hidden node index and specific training sample index respectively are used to model the system. To convert a node's input signal to an output signal, as well as ensure non-linearity of the network, a hard limit activation function is integrated.

To train $SimNet$, each input value fed into the neural network is multiplied by its weights ($\omega_i \times x_j$). This is then

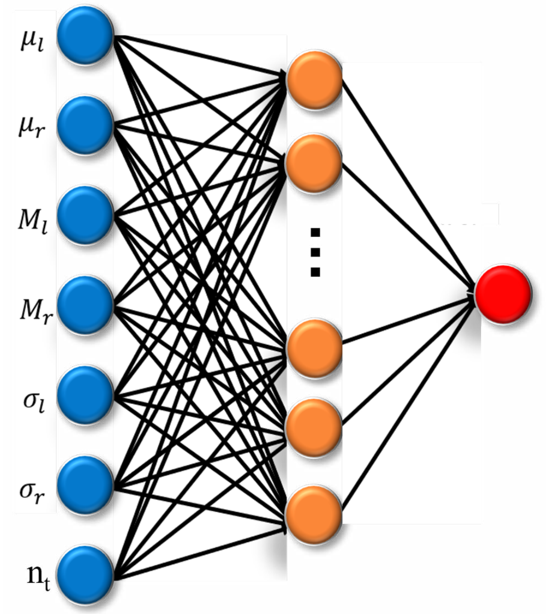

Fig. 2. SimNet Structure for pose estimation of sensor nodes

summed with the hidden nodes bias (b_i) value. The resultant becomes the input for the hard-limit activation function. Since the model is a supervised machine learning model, we set the output layer to the same target output. The log shadowing path loss model is used to calculate the RSSI value as summarized in equation (5):

$$\begin{gathered}\xi(\partial_x) = \xi_0 + 10.\pi.log_{10}(\frac{\partial_x}{\partial_0}) + \phi_n, \\ R_{(t)} = R_{(g)} + (U_{(g)} - \xi(\partial_x)),\end{gathered} \tag{5}$$

where $\xi(\partial_x)$ = path loss at a defined distance, ∂_x; ξ_0 = reference distance ∂_0 path loss; π = path loss co-efficient; ϕ_n = noise from Gaussian distribution with zero μ and σ value; $R_{(t)}$ = RSSI value; $R_{(g)}$ = sensor node antenna/receiver gain; and $U_{(g)}$ = gain from antenna / transmitter UAV. Hence, the value of path loss, $\xi(\partial_x)$ is dependent on the environmental parameters; ξ_0, π, and ϕ_n while the values of $R_{(g)}$ and $U_{(g)}$ are constant. Simulation is performed in Python environment on a Windows 10 operating system with the hardware configuration of Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz, 6Core(s), NVIDIA GeForce GT 1030, GPU CUDA:0 (Tesla K80, 11441.1875MB) and 36GB RAM.

III. Result and Performance Evaluation

The results of the simulation and performance evaluation are presented forthwith as summarized in Table I, Table II, Fig. 3, Fig. 4, and Fig. 5 for training and testing of the proposed model with similar localization schemes; Support Vector Machine (SVM) and Backpropagation (BP) respectively. The results in Table I show that SimNet achieved better performance than the

TABLE I
Performance of Models

Time (s)/Model	**Proposed (SimNet)**	SVM	BP
Training Time	**0.00320**	0.191	0.152
Testing Time	**0.00039**	0.00099	0.0164

SVM and BP learning algorithms with a faster training time value of $0.00320s$ and a testing time of $0.00039s$.

Furthermore, the localization errors of the models for both the training and testing stage, as seen in Fig. 3 show the performance of each model indicated by the regression lines. The red, blue, and black dots are the localization errors during the training and testing of the SimNet, SVM, and BP algorithms.

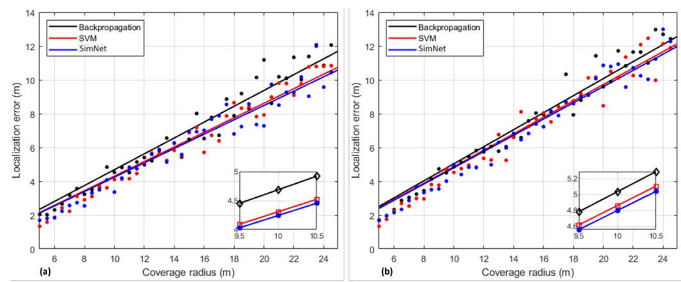

Fig. 3. Performance of learning algorithms showing (a) Graph of training errors and (b) Graph of testing errors

The results in Fig. 3 indicate that SimNet outperforms BP and SVM with the least localization training errors and testing errors and faster time, as indicated by the blue regression line and dots, respectively.

Also, to examine the effect of the hard-limit activation function on the proposed model, the result in Fig. 4 compares its performance with the Sigmoid and sine function respectively.

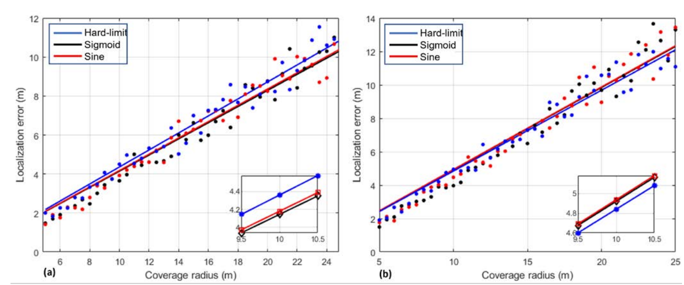

Fig. 4. SimNet performance showing (a) Graph of Training errors with different activation functions, (b) Graph of Testing errors with different activation functions

From Fig. 4(a), the results indicate that at the training stage, the hard-limit activation function had better performance. But at the testing stage, Fig. 4(a), the hard-limit activation function performance is poor.

Furthermore, to evaluate the reliability of the proposed model, the results in Fig. 5 show the performance of SimNet at different hidden nodes. The results of Fig. 5 show that the increase in the number of hidden nodes does not translate into an increase in the accuracy of SimNet's localization. Hence, the increase in the number of hidden nodes is immaterial in enhancing the localization accuracy performance of the proposed model. Thus, a low computational complexity is achieved with a faster time.

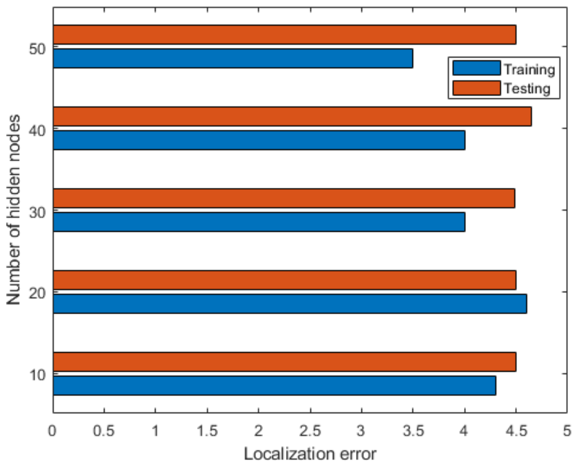

Fig. 5. (a)Performance of Proposed learning algorithm showing (a) Graph of Training errors of different hidden nodes (b) Graph of Testing errors of different number of hidden nodes

Finally, the results in Table II compare the performance of the proposed model with similar localization approaches based on existing works.

TABLE II
EVALUATION WITH SIMILAR LOCALIZATION SYSTEMS

	SimNet	[8]	[9]
Anchor node's type	**UAV**	Ground node	Ground node
Total anchor nodes	**2**	100	10
Deployment	**Fixed**	Random	Random
Localization error (m)	**1.7537**	3.6	6.45
GPS	**Not Needed**	Needed	Needed

In comparing the proposed model's performance with existing works, the result in Table II shows that SimNet is a better sensor node localization scheme with the least localization error of 1.75 without requiring GPS. These results undoubtedly, affirm SimNet as a low-computational and time-efficient UAV-integrated sensor nodes localization scheme for achieving communication intelligence in 6G networks where speed, smartness, and security are in tandem with intelligent connectivity in promoting drone transportation and other innovative 6G-enabled technologies.

IV. Conclusion

The article proposed a novel sensor node localization approach using neural networks and UAVs to achieve communication intelligence, low computational cost, and high-quality beacon signal receptivity. The result indicates that the proposed model achieved the stated peculiarities. However, there are some shortcomings. Future work will tend to expand the model to increase connected sensor nodes in the edge network and improve its performance for wide coverage.

Acknowledgments

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