Collaborative Localization Determination using Adaptive Deep Learning Algorithms for Wireless Sensor Network

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Abstract: The localization determination of Wireless Sensor Nodes in Internet of Things (IoT-WSN) has garnered significant attention in the research community due to its potential for valuable information and communication. To address the localization accuracy and privacy challenges, a novel solution called Deep Learning-based Collaborative Localization in IoT-WSN environments (DLCollLoc) has been proposed. DLCollLoc employs various range-based measurements to achieve high localization accuracy and resolves the privacy and localization error issues present in prior works. Additionally, the proposed approach optimizes the network topology initially through the ToPoNET framework based on a Voronoi structure, aiming to reduce energy consumption and enhance connectivity. Subsequently, anchor node deployment is conducted using the Upgraded Butterfly Backtracking Optimization (UBBO) algorithm. The pilot agents are responsible for clustering sensor nodes using the Enhanced Density Peak Clustering Algorithm (E-DenPeC), addressing device heterogeneity. For the clustered sensor nodes, localization is achieved using a Squeeze-Excitation Network embedded Skip Connection Gated Recurrent Unit and Accelerated Iterative Algorithm (SEN-GRU-AI), incorporating Five Different Localization Techniques (FLMT). Collaborative localization is then implemented using Deep Learning (DL) technology, selecting sub-anchors and collaboratively localizing unlocalized nodes to ensure privacy. The results demonstrate that the proposed approach surpasses existing methods in terms of performance.

Keywords: Wireless Sensor Networks (WSN), Internet of Things (IoT), Collaborative Localization, Range based Localization, Federated learning (FL), Artificial Intelligence (AI).

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1. Introduction

Advancements in communication, embedded computing, and sensor technologies have facilitated the deployment of Wireless Sensor Networks (WSNs) across diverse domains including environmental monitoring, defence surveillance, target tracking, user localization, disaster response and recovery, hazard detection, e-healthcare, crop monitoring, and beyond [1], [2]. Wireless sensor networks represent a dynamic technology that is increasingly integral to our daily lives. Positioning is a central process within WSNs that enables the identification of sensor node locations. Data acquired without location information is rendered useless regardless of the cost [3], [4]. This underscores the critical importance of the localization process within WSN and its related Internet of Things (IoT) applications. In WSNs, both anchor nodes and sensor nodes play important roles. Anchor nodes are equipped with Global Positioning System (GPS) technology, allowing their locations in the environment to be known [5]. However, integrating GPS technology into numerous sensor nodes is impractical due to high implementation costs and increased energy consumption. Therefore, localization of sensor nodes is achieved using various measurement techniques [6], [7]. Two distinct types of localization measurement techniques exist: range-based techniques and range-free techniques [8]. In range-based localization, the accuracy is significantly impacted by the placement of anchor nodes, especially when Line of Sight (LOS) conditions are not taken into account [9]. Many research efforts have positioned anchor nodes strategically to mitigate multipath effects and fading by ensuring Line of Sight (LOS). However, these studies often overlook important features and considerations. Additionally, factors such as network topology and device heterogeneity also play a role in influencing localization accuracy. Therefore, taking into account these perspectives, we have introduced a novel concept that integrates federated learning with the sensor node localization process to facilitate further advancements. Additionally, we have leveraged lightweight deep learning and optimization algorithms, along with a balloon mechanism, to significantly enhance the accuracy and performance of sensor node localization. The significant issues identified in prior works have motivated us to initiate research focused on localizing wireless sensor nodes within an IoT environment using deep learning and advanced localization measurement

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techniques. Our proposed research aims to address several existing problems, including ineffective anchor node positioning, high energy consumption, and a low localization success ratio. The primary objective of this study is to enhance localization accuracy and improve network coverage. To achieve this, we have designed the network topology and strategically positioned the entities within it. To streamline the localization process and increase the localization success ratio, we have effectively utilized localized information with the support of federated learning. Additionally, we have incorporated various localization measurement techniques to further enhance accuracy and efficiency.

2. Research Innovation

In this work, we propose a robust and privacy-preserving intelligent localization technique to enhance the resiliency of IoT-WSN environments. Some of the major contributions of this work are the connectivity, energy consumption issues, and coverage issues are resolved by proposing network topology construction. In order to resolve the multi path fading and path loss effects during localization, we have performed LOS aware anchor node placement using UBBO algorithm based on several metrics. The localization is achieved by adopting SEN-GRU-AI based FLMT technique in which AOA, ADOA, TOA, TDOA, and RSSI measures are adopted to robust localization. The collaborative localization is achieved by adopting selecting the already localized node as sub-anchors and results are continuously updated using FL technology.

3. Literature Survey

This section focuses on reviewing state-of-the-art research in localization techniques within IoT-WSN environments, employing AI and optimization-based methodologies for both range-based and range-free approaches. The brief review of existing literatures is listed below.

In this paper [10], the authors have introduced a framework for localizing wireless sensor nodes within an indoor environment by leveraging an artificial neural network (ANN) in conjunction with range-based measurements. In this work [11], the location of an unknown node was determined using a metaheuristic algorithm called grey wolf ant-lion, combined with a recursive model that utilizes a fitness function. The authors have achieved sensor node localization without the use of anchor nodes by leveraging base stations [12]. This research work [13] addressed the major limitation of relying solely on range metrics for localization, which led to reduced precision. The study focused on improving wireless sensor node localization by tackling issues related to non-line of sight (NLOS) conditions and high energy consumption. n this work [14], the authors proposed a concept that integrates the range-based localization technique using Angle of Arrival (AoA) with effective weighted least squares to accurately localize wireless sensor nodes. In this study [15], sensors utilizing infrared (IR) light were localized using the angle of arrival (AoA) technique. The localization process assumed that the anchors were strategically positioned to ensure line-of-sight (LOS) perspectives. The research focused on an indoor setting, specifically within a supermarket. The study by [16], utilized the Monte Carlo method for localizing sensor nodes in a wireless sensor network-based Internet of Things (IoT) scenario. This method was employed to enhance localization accuracy while also detecting malicious or affected nodes within the network. In this work [17], the authors employed optimization algorithms to enable range-free localization in wireless sensor network environments. Specifically, the study introduced four localization methods based on the particle swarm optimization algorithm. The utilization of zeroing neurodynamic models in range-based measurements enhances the convergence rate of localization. This work [18] incorporates range-based measurements such as time difference of arrival (TDoA) and angle of arrival (AoA). The zeroing neurodynamic model includes activation functions that can be applied alongside AoA and TDoA to achieve accurate localization and reduce error rates in various scenarios. In this work [19], the authors employed the Harris Hawk Optimization (HHO) algorithm for localization in wireless sensor networks. Initially, anchor nodes were deployed in a two-dimensional space. After placing the sensor nodes, the unlocalized node computed the received signal strength indicator. Subsequently, the Harris Hawk Optimization algorithm was utilized to perform the node localization based on this received signal strength information. In this paper [20], the authors introduced a framework focused on localizing wireless sensor nodes using a range-based measurement technique. The received signal strength indicator (RSSI) from anchor nodes was utilized, and unknown nodes were localized using an optimization algorithm called Most Valuable Player (MVP). In this work [21], an enhanced metaheuristic algorithm was proposed for localizing wireless sensor nodes by transforming the localization problem into an optimization problem. Initially, sensor nodes and location-aware anchor nodes were randomly deployed. Additionally, it was assumed that all sensor nodes have a uniform communication range. In this study, the authors applied an enhanced particle swarm optimization (PSO) technique for localizing unknown sensor nodes [22]. They introduced a process called sensor node segmentation using PSO to improve localization accuracy. In this work [23], a hybrid localization approach combining four techniques—RSSI (Received Signal Strength Indicator), TDoA (Time Difference of Arrival), ToA (Time of Arrival), and AoA (Angle of Arrival)—was employed to localize unknown sensor nodes. The likelihood of each localization technique was determined using an estimation method called supreme likelihood. In this work, to optimize the output from the combination of these localization measures, an iterative algorithm called majorization and minimization was applied. However, the localization performance was hindered in this study due to limited convergence on resource-constrained nodes.

4. Methodology

The objective of localization in IoT-based Wireless Sensor Networks (WSNs) is to precisely determine the positions of unknown sensor nodes using diverse range-based methods. Let's examine an m-dimensional IoT-based WSN scenario comprising L anchor nodes and multiple unknown nodes (i.e., nodes whose positions are not yet determined) within a 3D coordinate space (x, y, z). The position of the j^{th} anchor node defined as $an_i = [an_{xj}, an_{yj}, an_{zj}]^T \in \mathbb{R}^l, j \in L \triangleq \{1, \ldots, L\}$. On the other hand, the unknown sensor node positions are shows as $O = [O_x, O_y, O_z]^T \in \mathbb{R}^l$. In general, the unknown sensor node located in the two or more-anchor node transmission range is considered as localized. During, localization every O computes the distance in terms of NLOS from the anchor node that can be formulated as,

$$dis_{NLos} = dis_i + no_i + err_{NLos} \tag{1}$$

Where, dis_i is the distance computed by the i-th unknown sensor node, err_{NLos} is the error during NLos, and no_i denotes the Gaussian noise. The anchor node continuously transmits a signal in its transmission range. The unknown sensor node, received the signal information and measured the path loss (PL) based on different measurement techniques. Let the j-th anchor node measures the range information using different measurement techniques can be formulated as,

$$RSSI \rightarrow PL_j = PL_0 + 10\gamma \log_{10}\|O - an_j\| + no_{RSSI_j} \tag{2}$$

From the above equation, no_{RSSI_i} denotes the RSSI noise, the exponent of path loss is denoted as γ, and PL_0 denotes the path at reference distance dis_j. The AOA and ADOA measurement for the j-th anchor node can be formulated as,

$$AOA \rightarrow \begin{cases} \emptyset_j = \tan^{-1}\left(\frac{O_y - an_{yj}}{O_x - an_{xj}}\right) + no_{AOA_j} \\ \theta_j = \cos^{-1}\left(\frac{O_z - an_{zj}}{\|O - an_j\|}\right) + no_{AOA_j} \end{cases} \tag{3}$$

$$ADOA \rightarrow \begin{cases} \emptyset_{(j-2\pi)} = \tan^{-1}\left(\frac{O_y - an_{yj}}{O_x - an_{xj}}\right) - \|O\| + no_{AOA_j} \\ \theta_{(j-2\pi)} = \cos^{-1}\left(\frac{O_z - an_{zj}}{\|O - an_j\|}\right) - \|O\| + no_{ADOA_j} \end{cases} \tag{4}$$

From the above equations (3) and (4), $\emptyset_j$ and θ_j defines the azimuth and elevation angles, $\emptyset_{(j-2\pi)}$, and $\theta_{(j-2\pi)}$ azimuth and elevation delay angles for ADOA measurements. The noise in the AOA and ADOA is denoted as no_{AOA_j} and no_{ADOA_j} respectively. The TOA and TDOA measurements for the j-th anchor can be formulated as,

$$TOA \rightarrow ct_j = \|O - an_j\| + no_{TOA_j} \tag{5}$$

$$TDOA \rightarrow c(t_j - t_0) = \|O - an_j\| - \|O\| + no_{TDOA_j} \tag{6}$$

Where,no_{TOA_j} and no_{TDOA_j} denotes the noises in the time measurement for TOA and TDOA respectively. t_j and t_0 are the delay propagation at the j-th anchor node, and c is the signal speed. From the equation (2), (3), (4), (5) and (6) the joint probability measure can be computed in together by,

$$pr(RSS, AOA, ADOA, TOA, TDOA|O) = pr\left(\frac{RSS}{O}\right) pr\left(\frac{AOA}{O}\right) pr\left(\frac{ADOA}{O}\right) pr\left(\frac{TOA}{O}\right) pr\left(\frac{TDOA}{O}\right) \tag{7}$$

However, the adoption of five different measurement for node localization leads to majorization minimization problem which can be overlooked by minimizing and maximizing some of the objectives. The objectives are listed as follows,

$$mini \rightarrow \{Ene, Cost, loc_{err}\} \tag{8}$$

$$maxi \rightarrow \{sec, pri\} \tag{9}$$

Where, eqn (8) denotes the minimization of energy consumption, cost, and error during localization respectively. Whereas, eqn (9) denotes the maximization of security and privacy respectively.

5. Proposed Work

This study is entirely focused on localizing unidentified IoT sensor nodes within a Wireless Sensor Network (WSN) aided by latest technology, employing Ultra-Wide Band (UWB) and Federated Learning (FL). The fig 1 represents the overall architecture of the proposed FL based localization model using UWB.

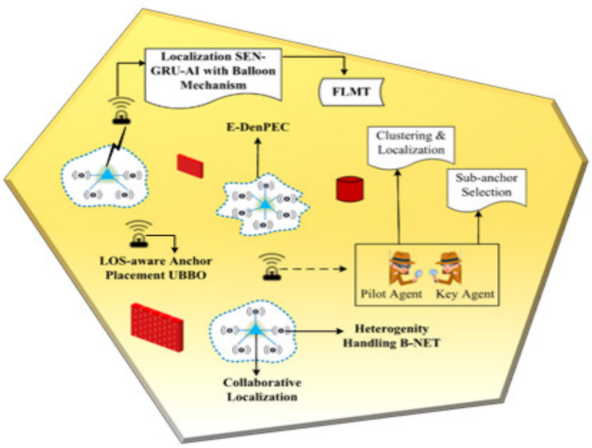

Fig.1. Overall Architecture of the Proposed DLCollLoc

6. Simulation Work

The DLCollLoc method is designed to enhance localization accuracy and reduce localization errors while incorporating security and privacy measures. This method is validated and simulated using the Network Simulator 3.26 (NS-3.26) simulation tool. To achieve improved simulation outcomes, we adjusted both system configurations (as detailed in Table 1) and simulation settings (as outlined in Table 2).

Table 1 System Setting

Software Configurations	CPU	Intel(R) Core (TM) i5-4590S CPU @ 3.00GHz 3.00 GHz
	Operating System	Ubuntu 14.04 LTS
	Simulation Tool	NS-3.26
Hardware Configurations	Hard disk Capacity	500GB
	Random Access Memory	4GB

Table 2 Simulation Settings

Simulation Parameters	**Values**
# of Anchor Nodes	5
# of Unlocalized Nodes	50
# of Sub-Anchors	35
Simulation Environment	$250 \times 250\text{m}^2$
Time for Simulation	200s
Mobility Model of Anchor/Sub-Anchor Nodes	Random Way Point
Mobility Model of Unlocalized Nodes	Random Way Point
Signal Propagation Range	500m (all directions)
Energy Consumption During Transmission	1.75W
Energy Consumption During Reception	0.5W
Measurement Methods	RSSI, TOA, TDOA, AOA, and ADOA
Iteration During Localization	5,10,15, 20, 25
Initial Energy Consumption	50J

7. Result Analysis

In this section, we conduct a comparative analysis of the DLCollLoc method with existing approaches such as Received Signal Strength Indicator (RSSI) - Most Valuable Player Algorithm (MVPA) [28] and Enhanced Cuckoo Search algorithm ECSA [29]. We validate and assess these methods based on metrics including localization error and energy consumption.

The localization success rate is determined as the ratio of incorrectly estimated localization results to the total number of anchor nodes in the environment. The incorrect estimations are identified based on the root mean square error (RMSE).

The mathematical formulation of Localization Error (LE) can be expressed as,

$$\text{LE} = \frac{\text{rmse}}{\text{an}_\text{m}} \times 100 \tag{10}$$

Where, rmse is defined by $\sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_i - \varphi)^2}$ in which n represents the number of anchor nodes, y_i is the data for localization, φ denotes the location of the unlocalized node, and an_m is the total number of anchor nodes.

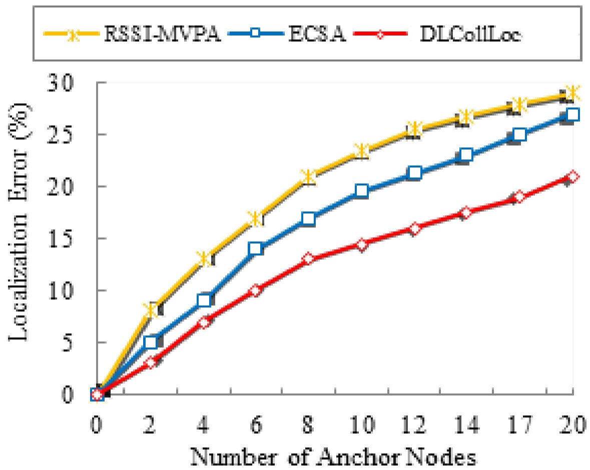

Fig.2. Number of Anchor Nodes Vs Localization Error (%)

The comparison of LE with number of anchor nodes for the proposed DLCollLoc and existing works ECSA, and RSSI-MVPA is shown in fig 2. The graphical plot shows that, the proposed work achieves lesser LE when compared to the existing works. The reason for such lesser LE is that, the proposed work enables collaborative localization using federated learning methodology by selecting already localized node as sub-anchors.

Comparison of Energy Consumption

The amount of energy consumed by the WSN-IoT nodes in the environment during localization process. The Energy Consumption (EC) can be formulated as,

$$\mathrm{EC} = \mathrm{ToT}_{\mathrm{ene}} - \mathrm{Con}_{\mathrm{ene}} \tag{11}$$

Where, $\mathrm{ToT}_{\mathrm{ene}}$ is the total energy of the WSN-IoT nodes, and $\mathrm{Con}_{\mathrm{ene}}$ is the consumed energy of WSN-IoT nodes.

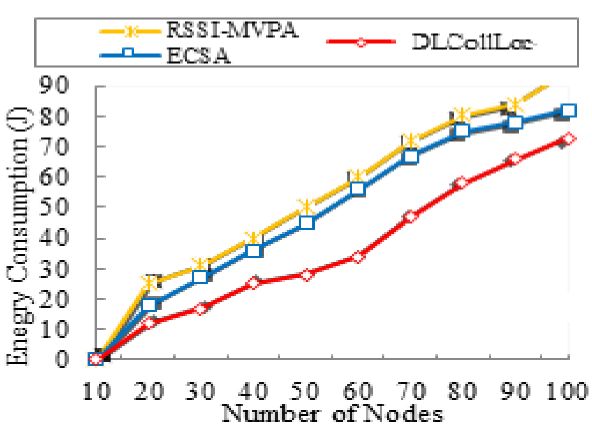

Fig.3. Number of Nodes Vs Energy Consumption (J)

The comparison of EC with number of nodes for the proposed DLCollLoc and existing works ECSA, and RSSI-MVPA is shown in fig 3. From the inference it is shown that, the proposed work gains lesser energy consumption than the proposed work. The reason for such decrement in energy consumption is that, the proposed work performs clustering of WSN-IoT nodes based on device heterogeneity and orientation using E-DenPeC algorithm.

8. Research Summery

In this study, the topology of the IoT Wireless Sensor Network (WSN) is configured using a Voronoi structure facilitated by a lightweight B-NET algorithm. This approach enhances network representation while mitigating computational complexities, thereby achieving robust connectivity and network coverage by taking range into consideration.

Intelligent anchor nodes were deployed in a LOS-aware manner by considering different features such as obstacles (size and shape), terrain, signal propagation, delay, distance, link quality, CSI, and path loss with the help of the UBBO algorithm.

To reduce energy consumption and enrich the localization accuracy, sensor nodes are clustered using the E-DenPeC which degrades computational complexity.

Conclusion

The main challenges in a Wireless Sensor Network (WSN) IoT localization environment include elevated localization errors, concerns regarding privacy, increased energy consumption, and higher computation overhead.

The proposed approach utilizes the B-NET algorithm to construct the network topology in a Voronoi structure based on the range of anchor nodes.

In this context, the proposed work employs the UBBO optimization algorithm, which considers various metrics including obstacles (size and shape), terrain characteristics, signal propagation properties, delay, distance, link quality, Channel State Information (CSI), and path loss to optimize the network topology construction and ensure effective performance.

At last, the node localization is enabled by adopting SEN-GRU-AI algorithm which accurately localizes the unlocalized nodes using FLMT technique.

The comprehensive simulation results demonstrate that the proposed localization method outperforms existing approaches in all evaluated aspects.

Table 3 Results Comparison of Proposed Vs Existing

Performance Metrics	RSSI-MVPA	ECSA	Proposed Work (DLCollLoc)
Localization Error (%)	0.4 ± 19.162	0.2 ± 16.09	0.1 ± 12.1
Energy Consumption (J)	0.15 ± 53.76	0.3 ± 48.4	0.4 ± 36

The current challenges Higher localization error, privacy, energy consumption, and computation overhead are the major issues of WSN localization and these are addressed through the implementation of the DLCollLoc approach, integrating FL, and AI technologies to achieve a strong and intelligent localization framework. The proposed work utilizes the B-NET algorithm to construct the network topology in a Voronoi structure based on the range of anchor nodes. To enhance localization accuracy and achieve faster results, we implemented FL-based collaborative localization. This involved selecting already localized nodes as sub-anchors, facilitating easier and more efficient localization. The comprehensive simulation results demonstrate that the proposed localization method outperforms existing approaches in all evaluated aspects.

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