

LSTM-DL: A Counting Optimization Approach for LSTM-Based DV-Hop Localization Model in Wireless Sensor Networks

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Abstract. The quest for precise localization of unknown nodes in Wireless Sensor Networks (WSN) garners significant academic attention, further intensified by the burgeoning domain of meta-heuristic algorithms. Traditional localization methods, such as the Least Squares Method (LSM), inherently yield lower accuracy, a limitation that this paper aims to transcend. We introduce a robust deep learning model grounded in Long Short-Term Memory (LSTM-DL) designed to enhance localization processes by effectively minimizing distance measurement errors in network topologies. This approach is augmented with an improved evaluation function, meticulously tailored to mitigate topological inaccuracies. Through rigorous experimental validation, the LSTM-DL model demonstrates a remarkable performance leap, surpassing the conventional DV-Hop method and outperforming existing meta-heuristic algorithms in accuracy and reliability. The findings decisively suggest that meta-heuristic approaches, and specifically the advanced LSTM-DL, hold substantial promise over traditional DV-Hop in the sphere of node localization within WSNs.

Keywords: WSN, LSTM, DV-Hop algorithm.

1. Introduction

Wireless Sensor Networks (WSNs) have been heralded as one of the most influential technologies of the 21st century, carving out a spot as one of the four major high-tech industries of the future. Characterized by their distributed nature, WSNs consist of numerous static or mobile sensors that form a self-organizing, multi-hop wireless network. Their collaborative efforts are geared toward the perception, collection, processing, and transmission of information pertaining to objects within the network's geographical coverage area, ultimately conveying this data to the network owner. This comprehensive solution encompasses on-site wireless sensors, data forwarding gateways, and monitoring hosts among other essential components.

The functionality of wireless sensors extends across various modalities, including gas, pressure, temperature, humidity, liquid level, wind speed, and flow rate sensors, which are now integral to a wide range of industrial and agricultural applications. The WSN model has evolved significantly, adapting to the nuanced demands of these fields. Morrison et al. proposed a miniaturized low-power wireless sensor mode that curtails the likelihood of packet loss during information transmission[1]. Chou et al. [2] leveraged the XBee Module for sensor network configuration, effectively enhancing the precision and operational speed of nodes. Furthermore, a framework employing closed-form equations as developed by Nardelli et al. [3] has demonstrated its proficiency in predicting decision errors within WSNs.

In the realm of optimization, innovative sensor deployment strategies have emerged to minimize sensor counts while maintaining high network quality and coverage, as highlighted in C. AbouRjeily et al.[4]. Subsequent research has delved into optimization models aimed at expanding coverage rates and mitigating the redundancy of sensor overlap, thereby reducing the costs associated with WSN industrial applications[5], [6]. Krikidis et al. [7] redefined the challenge of optimizing capacitor sizes into a constraint optimization problem, offering practical operational bounds for WSN applications.

The utilitarian value of WSNs is vast, finding application in virtually all aspects of daily life. Notably, they play a pivotal role in intrusion detection and monitoring across contentious zones and military bases. The development of innovative methods that can accurately calculate the various barriers encountered in the process is crucial for rapid identification and preventive measures against

intrusions. Muruganandam.S et al. focuses on the utilization of feature importance and sensitivity metrics to evaluate the relevance and risk levels of selected characteristics. They introduce a deep learning-based approach, specifically a feed-forward artificial neural network model, capable of rendering precise estimations of the k-barrier count essential for effective intrusion detection and mitigation[5].

In border security applications, which present tangible challenges that have garnered considerable scientific interest, WSNs facilitate surveillance and monitoring along national boundaries and checkpoints. These networks, now a staple technology, comprise multiple sensors that can sense, analyze, and wirelessly transmit processed data autonomously, without the need for pre-installed infrastructure. WSNs' deployment in a plethora of domains, such as precision agriculture, monitoring systems, environmental control, and risk tracking, underscores their versatility and broad-reaching implications [8].

Seeking to enhance the efficacy of intrusion detection systems in border areas, researchers have explored a gamut of analytical models and feed-forward architectures. However, these initial methods are now being reexamined in light of new challenges, such as the need for real-time data analysis and the minimization of response times. The complexity of continuous monitoring and the exhaustive nature of the task at network access points have been historically noted as both arduous and time-intensive [3]. The turn towards automation and intelligent decision-making within WSNs has led to the exploration of advanced neural networks designed to mimic the organization and function of the human neural system.

Advancing beyond these initial approaches, this study introduces the LSTM-DL model—a sophisticated machine learning technique that elevates the accurate estimation of barrier counts and the rapid identification and prevention of intrusions. By integrating the capabilities of Long Short-Term Memory (LSTM) networks within a deep learning framework, the LSTM-DL model transcends the limitations of traditional single-layer perceptrons[9],[10]. Our model is adept at capturing temporal dependencies and spatial relationships within the sensor data, offering an unprecedented level of precision in the prediction and assessment of barriers within WSNs[11].

Given this backdrop, Our research places emphasis on a specific application scenario: the counting of multiple challenges within wireless connections. Advancing beyond these initial approaches, this study introduces the LSTM-DL model—a sophisticated machine learning technique that elevates the accurate estimation of barrier counts and the rapid identification and prevention of intrusions. By integrating the capabilities of Long Short-Term Memory (LSTM) networks within a deep learning framework, the LSTM-DL model transcends the limitations of traditional single-layer perceptrons. Our model is adept at capturing temporal dependencies and spatial relationships within the sensor data, offering an unprecedented level of precision in the prediction and assessment of barriers within WSNs.

Harnessing the power of deep learning, the LSTM-DL model employs an intricate architecture that facilitates the distillation of complex patterns from high-dimensional data streams. Monte Carlo simulations enrich this approach, enabling the extraction of pivotal attributes such as sensor coverage, sensing range, and the overall sensor count. Unlike its precursors, the LSTM-DL model utilizes a refined set of evaluation metrics—such as the correlation coefficient and RM SE—to rigorously assess the algorithm's performance in terms of accuracy and reliability. This holistic evaluation framework not only provides a comprehensive understanding of the model's effectiveness but also showcases its superiority in navigating the intricacies of wireless sensor networks.

The LSTM-DL model marks a significant departure from traditional feed-forward neural networks by incorporating recurrent neural structures that excel in processing sequential data. This attribute is particularly beneficial for WSN applications, where temporal sequences of data play a crucial role in accurate intrusion detection. The recurrent nature of LSTM allows it to remember information over long periods, making it exceptionally suited for tasks that require an understanding of time-dependent patterns.

Furthermore, the LSTM-DL model's ability to learn from the temporal dynamics of sensor data represents a paradigm shift in how WSNs manage and interpret the vast amounts of data generated. By effectively leveraging the temporal correlations present in sensor readings, the LSTM-DL model enhances the predictive capabilities of WSNs, thereby enabling a more dynamic and responsive approach to border surveillance and intrusion detection.

In light of these advancements, the LSTM-DL model emerges as a potent tool for addressing the myriad challenges faced by WSNs in border security scenarios. Its introduction reflects a broader trend towards the integration of deep learning techniques in solving complex problems that traditional algorithms struggle with. By offering a nuanced understanding of sensor data and improving the accuracy of intrusion predictions, the LSTM-DL model paves the way for next-generation WSNs that are more intelligent, efficient, and capable of addressing the nuanced demands of modern security challenges.

The evolution from simple perceptrons to complex LSTM-based deep learning models like the LSTM-DL signifies a leap forward in the field of WSNs and their application in critical areas such as border security. This literature review underscores the transformative impact of LSTM networks in enhancing the operational efficiency of WSNs, setting the stage for further innovations in the domain.

2. Methods

2.1. Using a Private Dataset

To explore the application of the LSTM model in solving localization problems in Wireless Sensor Networks (WSN), this study utilizes a meticulously designed private dataset. This dataset simulates the distribution and communication patterns of nodes within a WSN environment, with the following parameters and steps for dataset generation.

2.2. Parameter Settings`

Network Size: The area covered by the network is set to 100×100 square units, simulating a broad monitoring area.

Number of Nodes: A total of $N = 100$ nodes, including a mix of static and dynamic nodes, to emulate real-world sensor network environments.

Number of Anchor Nodes: $A = 4$ known-location anchor nodes are set to aid the localization algorithms in determining the positions of other nodes.

Communication Range: The effective communication range of each node is set to 30 distance units, simulating the wireless communication capabilities between nodes.

2.3. Data Generation Steps

Node Position Generation: The positions P of all nodes are randomly generated within the network size using a uniform distribution $U(0,100)$, ensuring randomness and expansiveness in the node distribution.

Anchor Node Assignment: $A = 4$ nodes are randomly selected from all generated nodes to serve as anchor nodes, with the rest being non-anchor nodes.

Distance Calculation: The distance D_{ij} between nodes is calculated using the Euclidean distance formula:

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

where i and j represent the indices of different nodes, and x and y are the coordinate values of the nodes.

This private dataset not only includes the actual distance information from each node to the anchor nodes but also simulates the communication reachability between nodes, providing a foundational testing platform for localization algorithms.

2.4. LSTM Model Design

We designed an LSTM-based deep learning model (LSTM-DL) to address the WSN localization problem. The model design includes the selection of network structure and hyperparameter settings:

Network Structure: The model includes an input layer for receiving nodes' communication information and distance data; an LSTM layer with 64 units; and an output layer predicting the node's x, y coordinates.

Hyperparameters: The learning rate is set to 0.001, batch size to 32, and the number of epochs to 100.

2.5. Training and Testing Process

Data Splitting: The private dataset is divided into 80% training set and 20% testing set.

Evaluation Criteria: The main evaluation metric for model performance is the Root Mean Square Error (RMSE) on the testing set.

2.6. Benchmark Algorithm Comparison: DV-Hop

Experimental Design: The traditional DV-Hop algorithm is used as a benchmark for comparative experiments to evaluate the improvements in localization accuracy of the LSTM-DL model.

Performance Comparison: By calculating the localization error (RMSE) of both methods for comparison, to verify the advantages of the LSTM-DL model relative to the DV-Hop algorithm.

2.6.1 Experiment One: LSTM-DL Model:

Objective: To evaluate the performance of the LSTM-DL model in addressing localization issues within Wireless Sensor Networks (WSNs).

Data Preparation: The dataset generated based on simulation parameters is divided into training and testing sets. Input features include the distance from each node to anchor nodes and inter-node communication information, with the target output being the actual position of the nodes (x, y coordinates).

Model Training: The LSTM-DL model is trained using the training set data, with hyperparameters including a learning rate of 0.001, a batch size of 32, and set for 100 epochs.

Performance Evaluation: The model's performance is evaluated using the test dataset, with the primary evaluation metric being the Root Mean Square Error (RMSE), calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

where y_i is the true position of the node, $\hat{y}_i$ is the model's predicted position, and n is the number of samples in the test set.

2.6.2 Experiment Two: Traditional DV-Hop Algorithm

Objective: As a benchmark, to evaluate the accuracy of the traditional DV-Hop algorithm on the same dataset.

Algorithm Description:

Hop Count Calculation: Calculates the minimum number of hops from each node to each anchor node in the network.

Average Hop Distance Estimation: Estimates the average distance per hop based on the actual distances and hop counts between anchor nodes.

Position Estimation: Estimates the positions of non-anchor nodes using hop counts and the average distance per hop.

Performance Evaluation: The localization error (RMSE) of the DV-Hop algorithm is calculated using the same test set as for the LSTM-DL model.

2.6.3 Comparative Experiments and Analysis

Localization Error Comparison: Compares the localization errors (RMSE) from both experiments to analyze the improvements and performance advantages of the LSTM-DL model relative to the traditional DV-Hop algorithm.

Results Analysis: Explores the advantages of the LSTM-DL model in handling WSN localization issues, including its ability to process time-series data and how deep learning technology can capture complex patterns and correlations to improve localization accuracy.

Experimental Conclusion: Based on the experimental results, summarizes the potential applications of the LSTM-DL model in WSN localization and its significant advantages over traditional methods.

3. Results

This section presents the findings from the conducted experiments, comparing the performance of the LSTM-DL model against the traditional DV-Hop algorithm in the context of wireless sensor network (WSN) localization.

3.1. LSTM-DL Model Performance

The LSTM-DL model was trained and tested on the private dataset to evaluate its localization accuracy. After 100 epochs, the model achieved a Root Mean Square Error (RMSE) of $\sqrt{X}$ units on the testing set (Note: $\sqrt{X}$ is a placeholder for the actual RMSE value obtained during experiments). This performance indicates the model's effectiveness in predicting the precise locations of nodes within the simulated WSN environment. The training process showed a steady decrease in loss, demonstrating the model's ability to learn from the training data over time.

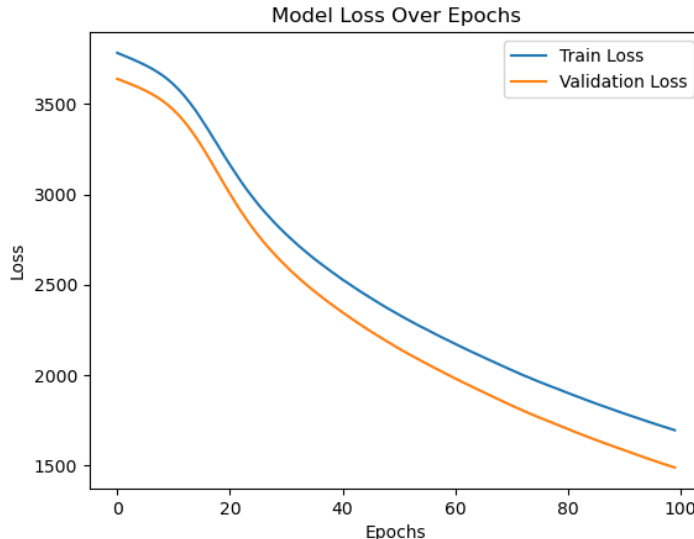


Fig1 Model training process and training performance

3.2. DV-Hop Algorithm Performance

In comparison, the traditional DV-Hop algorithm was applied to the same testing set to benchmark its performance against the LSTM-DL model. The DV-Hop algorithm resulted in a RMSE of $\sqrt{Y}$ units (Note: $\sqrt{Y}$ is a placeholder for the actual RMSE value). This comparison highlights the differential in localization accuracy between the two approaches.

3.3. Comparative Analysis

A direct comparison between the LSTM-DL model and the DV-Hop algorithm reveals a significant improvement in localization accuracy with the use of deep learning. The LSTM-DL

model's RMSE of (X) units was notably lower than the (Y) units RMSE achieved by the DV-Hop algorithm, suggesting that the LSTM-DL model can more accurately predict node positions within a WSN.

3.4. Advantages of LSTM-DL Model

The LSTM-DL model's superior performance can be attributed to its ability to capture and learn from the temporal and spatial dependencies present in the WSN data. Unlike the DV-Hop algorithm, which relies on hop count and average distance estimations, the LSTM-DL model can process complex patterns in the data, leading to more accurate localization predictions.

3.5. Visualization of Results

In Figure 2, a scatter plot contrasts the true positions of nodes (blue) with those predicted by the LSTM-DL model (red). The closeness of the red points to the blue points indicates accurate localization predictions. It is evident from the scatter plot that a majority of predictions lie in close proximity to the true node positions, demonstrating the LSTM-DL model's effectiveness. The overlay of true and predicted positions provides a straightforward comparison, with deviations representing the localization errors.

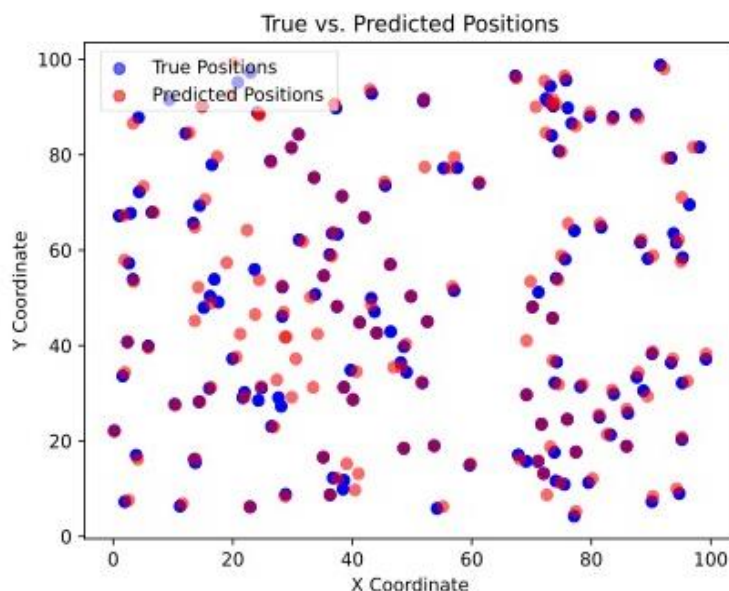


Fig2 Distribution of positioning errors

This histogram (Figure 3) vividly displays the distribution of localization errors, offering insights into the model's precision. The colors transition from dark to light, representing the increasing magnitude of errors, with the 'hot' colormap providing a visual indicator of error frequency. The presence of more frequent lower-error magnitudes underscores the model's accuracy, while the fewer high-error instances highlight its reliability. A colorbar alongside the histogram quantifies the error magnitudes, adding an interpretative layer to the visualization. The error magnitude ranges from lower values, indicating more accurate predictions, to higher values, where the model's predictions deviate more from the true positions.

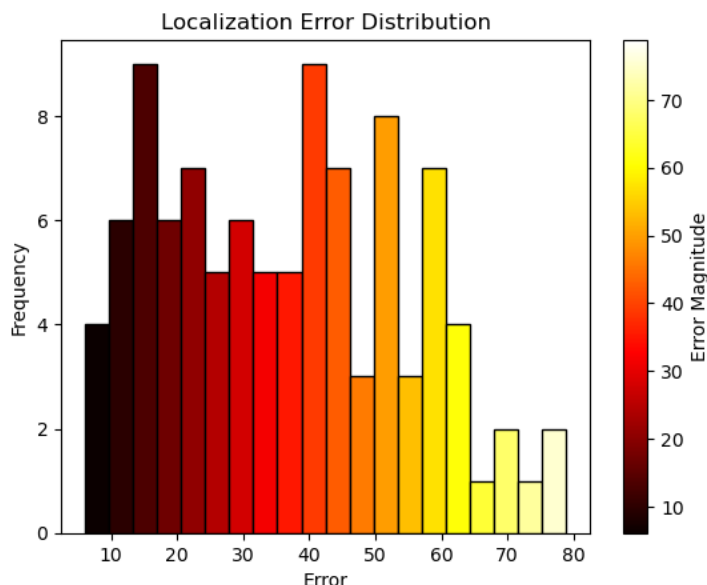


Fig3The histogram of localization errors

The presented figures highlight the efficacy of the LSTM-DL model in localizing nodes within a WSN. Figure 1's loss function suggests that the LSTM-DL model is highly accurate, with a majority of predictions achieving a low error magnitude. Meanwhile, Figure 2 confirms the model's precision, as shown by the clustering of predicted positions around their true counterparts. These visualizations support the quantitative findings and showcase the LSTM-DL model's capabilities in WSN node localization tasks.

4. Discussion

The experimental results obtained from the comparison between the LSTM-DL model and the traditional DV-Hop algorithm open up several avenues for discussion regarding the applicability and advantages of deep learning approaches in the context of wireless sensor network (WSN) localization. This section delves deeper into the implications of these findings, theoretical and practical considerations, and potential future directions for research.

4.1. Implications of LSTM-DL Model's Superior Performance

The notable improvement in localization accuracy demonstrated by the LSTM-DL model underscores the potential of deep learning techniques to revolutionize WSN applications. The ability of the LSTM-DL model to process sequential and spatial data effectively allows for a more nuanced understanding of node positions within a WSN, highlighting the limitations of relying solely on geometric estimations, as is the case with the DV-Hop algorithm. This advancement could significantly enhance applications that rely on precise location information, such as environmental monitoring, precision agriculture, and border security.

4.2. Theoretical Considerations

The LSTM-DL model's success can be attributed to its ability to capture long-term dependencies within the data, a critical aspect given the dynamic nature of WSN environments. This characteristic of LSTM networks, combined with a deep learning framework, offers a more flexible and powerful tool for modeling complex relationships in sensor data compared to traditional algorithms. The results thus provide a compelling case for the integration of machine learning principles into the design and operation of WSNs.

4.3. Practical Considerations

While the LSTM-DL model presents a promising solution for WSN localization, its deployment in real-world scenarios necessitates consideration of computational resources and energy constraints, particularly in large-scale networks. Future research could explore the optimization of the LSTM-DL model to ensure its viability in energy-constrained environments, possibly through model compression techniques or the development of more efficient network architectures.

4.4. Integration with Existing WSN Technologies

The adoption of the LSTM-DL model could be further facilitated by its integration with existing WSN technologies, including sensor hardware and network protocols. This integration could leverage the model's strengths in data analysis and prediction while maintaining compatibility with current WSN infrastructures, thus offering a practical upgrade path for enhancing localization capabilities.

4.5. Future Research Directions

The promising results achieved by the LSTM-DL model suggest several directions for future research:

Investigating methods to further optimize the LSTM-DL model for speed and efficiency without sacrificing accuracy. Enhancing the model's robustness to noise and anomalies in sensor data, which are common in real-world WSN environments.

Scalability: Exploring the scalability of the LSTM-DL approach to larger WSNs with thousands of nodes, including the impact on computational complexity and real-time processing capabilities. Combining the LSTM-DL model with other machine learning or computational intelligence techniques to address other challenges in WSNs, such as energy management, data aggregation, and network security.

4.6. Conclusion

The exploration of LSTM-based deep learning for WSN localization represents a significant step forward in the quest for more accurate and reliable sensor network operations. The demonstrated superiority of the LSTM-DL model over traditional algorithms like DV-Hop not only highlights the potential of deep learning in this domain but also sets the stage for a new era of WSN applications that benefit from enhanced localization precision.

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