Coverage Hole Detection using Deep Learning Models

Kareem Abrahim Kareem
Kufa University College of Agriculture
Kufa University
Najaf, Iraq
kareemsport2014@gmail.com
https://Orcid.org/0009-0005-6458-0205

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Abstract— *Wireless Sensor Networks (WSNs) function as essential components for contemporary systems because they serve multiple applications including environmental tracking and disaster control systems and modern smart urban planning and military field surveillance. WSNs face an essential challenge because sensor nodes are deployed randomly while environmental factors and battery drain and physical damage lead to node failures. Coverage holes which are areas without sensor monitoring create severe performance problems that affect data collection and routing efficiency and energy usage. Modern research focuses on three approaches for hole detection and repair in WSNs which involve computational geometry as well as statistical paradigms and topological analysis methods. The established techniques of Voronoi tessellation and Delaunay triangulation efficiently work on structured conditions yet fail to handle dynamic or irregular terrain situations.*

Deep learning solutions provide an effective answer to these difficulties through spatial-temporal hole identification capabilities. Both Convolutional Neural Networks (CNNs) extract spatial features present at node deployment maps and Transformers interpret temporal patterns that include node failures over time. The use of reinforcement learning approach enables optimal mobile node deployment through efficient movement to fix coverage deficits in real-time. This proposed algorithm combines the mentioned techniques to deliver advanced performance in detection accuracy with energy efficiency and better scalability for multiple environments. Results from simulations show that the proposed method improves current coverage hole solutions effectively by increasing coverage to access 98.6% while demonstrating consistent performance in resolving this widely known WSN problem.

Keywords— The research area includes Wireless Sensor Networks (WSNs), Coverage Holes, Deep Learning Models and Reinforcement Learning, Voronoi Tessellation and Delaunay Triangulation, Energy Efficiency and Spatial-Temporal Analysis.

I. INTRODUCTION

WSNs have established themselves as a revolutionary technology that implements connected sensor nodes across dynamic inaccessible environments for observation and information acquisition [1]. WSNs find practical applications throughout environmental monitoring together with [2] and healthcare as well as smart city implementations because these networks provide high scalability and flexibility. The complete coverage of Wireless Sensor Networks stands as a main concern because coverage holes which represent unmonitored areas by sensor nodes create serious network performance and reliability issues in extensive deployments. The resolution of this problem becomes vital because it enables enhanced data collection performance along with better energy usage and sustained network functionality [3], [4].

The detection of coverage holes has received extensive research using traditional geometric and heuristic methods [5]. The computational methods based on Voronoi diagrams and Delaunay triangulation help detection of coverage gaps through geometry techniques [6]. The structuring methods show reduced effectiveness when used in non-even node deployment situations that occur with dynamic and irregular terrains[7], [8]. The field of machine learning particularly through deep learning has brought new solutions to resolve these problems [9]. Researchers successfully developed better models for detection of coverage holes through network analysis of deep neural systems as they process spatial-patterns and temporal-dynamics [10].

The combination of convolutional neural networks (CNNs) for local details extraction applies together with either recurrent or transformer architectures for sequential pattern analysis. The predictive models accept various data including positional information and sensing radius data alongside residual energy values and environmental elements to deliver effective coverage gap detection [11]. Reinforcement learning techniques help optimize mobile sensor node movements to dynamically repair holes which have been detected by the system. A unified detection and repair system works to achieve complete network coverage by reducing energy usage [12].

As good as these developments are there are still issues that must be solved to use deep learning models on large-scale WSNs with difference node functionality and complex 3D structures. Future study needs to face difficulties that include managing high computational costs and maintaining real-time system performance and connecting edge computing functionalities to boost scalability and operational effectiveness.

Contributions- The proposed algorithm implements hybrid deep learning models to accomplish coverage hole detection and dynamic repair in WSNs. The proposed solution utilizes spatial-temporal analysis together with energy-aware optimization strategies to enhance network performance by improving accuracy while minimizing energy consumption in multiple operational scenarios.

II. RELATED WORKS

Wireless sensor networks (WSNs) underwent a development from geometry-based distributed protocols until the implementation of AI-derived solutions. This timeline includes essential contributions in the development of coverage hole detection for wireless sensor networks, Table 1 illustrates these contributions:

A. *Distributed Protocols (2016)*

A Distributed Coverage Hole Detection (DCHD) protocol based on perimeter detection was originally introduced by [13]. The method employed sensor coverage area geometric intersection to find holes while requiring no central coordination thus it saved power and reduced overhead compared to previous approaches.

B. *Computational Geometry (2017)*

Soundarya and Santhi designed a combined methodology which applies Delaunay Triangulation with virtual edge analysis for exact hole boundary detection. The new approach provided 18% better accuracy results compared to tree-based approaches while requiring the minimum number of redeployment nodes [14].

C. *RSSI Localization Enhancement (2018)*

The research team shaped their RSSI-based system by using Voronoi/Delaunay partitioning to assist with sensor

redeployment while using ellipses as the coverage model. Although it required fewer additional nodes than traditional disk models the proposed method successfully recovered total coverage areas [15].

D. *Clustering Innovations (2021)*

The researchers Wang & Hu developed a cluster-based detection framework through algorithm enhancements of k-means and DBSCAN algorithms. The system adopted cluster-head

coordination with boundary analysis for exact localization precision below 0.2R (sensing radius) [16].

E. *Deep Learning Breakthroughs (2022)*

Two landmark studies emerged:

FD-TL: Combined force-directed layouts with CNN transfer learning (90% sensitivity).

FD-CNN: Used pure topology analysis through CNN image recognition (80% sensitivity in <2 minutes)4
High accuracy operations became possible because GPS coordinates lost their necessity [17].

TABLE 1: WEBFLOW STRUCTURE FOR WIRELESS SENSOR NETWORKS (WSNS) MOVED PROGRESSIVELY FROM GEOMETRIC DISTRIBUTED PROCEDURES TO ARTIFICIAL INTELLIGENCE-BASED SYSTEMS. THE FOLLOWING TIMELINE FEATURES IMPORTANT WORKS AFTER THEIR REFINEMENT CHRONOLOGICALLY.

Year	Approach	Key Innovation	Performance Improvement	Source
2016	Distributed Protocols (DCHD)	Perimeter-based detection via geometric intersections of sensor coverage areas	Reduced power consumption by 22% vs. centralized systems	[13]
2017	Computational Geometry	Hybrid Delaunay Triangulation + virtual edge analysis	18% higher accuracy than tree-based methods	[14]
2018	RSSI Localization Enhancement	Ellipse-shaped coverage models with Voronoi/Delaunay partitioning	30% fewer nodes required for full coverage recovery	[15]
2021	Clustering Frameworks	Modified k-means + DBSCAN for cluster-head coordination	Localization errors <0.2R (sensing radius)	[16]
2022	FD-TL (Deep Learning)	CNN transfer learning + force-directed layout optimization	90% sensitivity, GPS-independent	[17]
2022	FD-CNN (Deep Learning)	Pure topology analysis via CNN image recognition	80% sensitivity in <2 minutes	[17]

III. ALGORITHM OVERVIEW

Deep CoverageNet: serves as a modern algorithm which uses deep learning models to perform accurate coverage hole discovery together with efficient network repair tasks in wireless sensor networks. It operates in three phases:

Phase 1: Coverage Hole Detection

1. Input Data:
   - The algorithm requires data from nodes including their positions as well as sensing radii and residual energy levels and RSSI values.
   - The detection of coverage holes depends on environmental factors which impact operational coverage.

2. Model Architecture:

   - The algorithm uses an integrated neural network structure by combining Transformer and CNN model features.
   - The analysis conducted by CNN identifies spatial properties that appear in node deployment maps including sensing coverage intersections.
   - Transformer identifies temporal patterns such as node failure patterns over time. Due to the computational overhead of Transformer models and energy budget of sensor nodes (100 Joules), the proposed algorithm uses' model compression. We employ a weight quantization technique to minimise the computational burden and a form of edge-offloading where the complex temporal analysis is delegated to the cluster heads, thus allowing real time inference without draining node batteries.

3. Output:
   - A probability map displays coverage depletion zones by coordinates along with scale-based severity rankings.

Phase 2: Coverage Hole Classification

1. Classification:
   A secondary neural network should analyze detected holes to establish their classification according to size together with impact severity:
   - Small holes (<10% of sensing area).
   - Medium holes (10–30%).
   - Large holes (>30%).

2. Prioritization:
   - A repair priority system should assign points for holes by combining their size dimensions with node density measurements and energy capacity considerations.

Phase 3: Dynamic Repair Using Reinforcement Learning.

1. **Agent Setup**:
   - The mobile network nodes serve the role of learning agents under a reinforcement learning system.

2. Reward Function Optimization:
The reward function is defined to balance coverage maximization and energy conservation. The weights are set to $\alpha = 0.6$ and $\beta = 0.4$ based on empirical tuning.
Coverage Gain (Δ C): Calculated as C_{new} - C_{old}, representing the additional area monitored after node relocation.

Energy Cost E_{move}): Defined as $E_{move} = k \cdot d$, where k is the energy consumption constant per meter and d is the displacement distance of the mobile agent.
Thus, the finalized reward function is: $R = 0.6 (\Delta C) - 0.4 . (k . d)$.

3. Action Space:
- Move toward hole centroids.
- The network adjusts sensor coverage range automatically to achieve maximum hole coverage while preventing redundancy issues.

4. Deployment Strategy:
- Mobile nodes should begin deployments by fixing large holes before moving onto the medium and small holes.

IV. SIMULATION SETUP

Deep learning models used for coverage hole detection get evaluated through an established simulation environment that duplicates Wireless Sensor Network (WSN) operational conditions. The simulation uses NS-3 network simulator and custom modules for deep learning-based coverage analysis to run the simulation based on the initial parameters used in
The system execution follows these procedures:

1. Network Initialization:
- A total of 500 sensor nodes operate within a 100m × 100m space. The dense node deployment (500 nodes) was chosen to represent a very crowded and harsh environment. In our simulation, we generated considerable "Obstacle Ratios" (buildings and trees) and "Signal Noise Factors" which can block sensing signals and shrink the effective sensing range of many nodes. This in turn introduces "shadow zones" or sensing holes in a dense deployment. Hence, the 98.6% improvement shows the effectiveness of the model in placing nodes in a complex environment where node density does not always ensure connectivity. The network distribution follows randomness while sensor nodes have different sensing radii that range from 5 to 10 meters.
- Every node starts with 100 Joules of energy during initialization.

2. Environment Configuration:
- Rephrase the following steps to simulate obstacles (such as buildings and trees) for generating realistic gaps in coverage.
- The analysis must consider external noise elements that result in signal degradation and signal disruption.

3. Deep Learning Integration:
- A Convolutional Neural Network (CNN) requires training on artificial datasets for detecting coverage holes.
- Reinforcement learning agents should dynamically repair holes that get detected through the network.
- We used a synthetic dataset that simulates different WSN deployment scenarios to train the CNN and Transformer models. We generated 10,000 samples, with each sample comprising of node locations, sensing range, and obstacle positions. The dataset was labeled by computing the actual coverage by using a fine-grained grid approach, where regions were labeled as 'covered' or 'hole' depending on the geometric overlap between the sensing ranges and obstacles. To avoid bias, the data was balanced to contain an equal mix of sparse and dense deployments over irregular terrains.

4. Performance Metrics:
- Perform an evaluation of detection performance alongside energy usage as well as analyze repair durations.

Initialization of Simulation are shown in the following Table 2.

TABLE 2: INITIALIZATION OF SIMULATION PARAMETERS

Parameter	Value	Description
Number of Nodes	500	Total sensor nodes deployed in the network.
Area Size	100m × 100m	Physical dimensions of the simulated area.
Sensing Radius	5–10 meters	Range within which nodes can detect events.
Initial Energy per Node	100 Joules	Energy available for each node at deployment.
Communication Protocol	IEEE 802.15.4	Standard protocol used for node communication.
Obstacles	Buildings, Trees	Simulated environmental factors causing gaps.
Noise Factors	Signal Attenuation, Interference	Environmental noise affecting signal quality.
Simulator	NS-3	Network simulator used for experimentation.
Deep Learning Model	CNN	Model trained to identify coverage holes.
Repair Mechanism	Reinforcement Learning	Agents dynamically repair detected holes.

V. COMPARATIVE SIMULATION RESULTS

The performance evaluation of Deep CoverageNet included comparison with three established methods including RSSI-based Ellipse Coverage Model [18] and Clustering Framework [19] and Energy-Efficient Deterministic Approach [20]. The simulation framework included 500 sensors randomly distributed across a 100m × 100m space containing obstacles which generated actual coverage areas. The evaluation used detection accuracy as well as energy consumption and repair time and coverage improvement measurements. **Error! Reference source not found.**, contains the comparative simulation results.

Deep CoverageNet achieved slightly better performance regarding detection accuracy and energy efficiency together with comparable repair duration relative to alternative methods. Accurate hole detection and dynamic reinforcement learning combine through the hybrid CNN-Transformer deep learning structure to yield these improvements.

TABLE 3 : COMPARATIVE SIMULATION RESULTS

Metric	Deep CoverageNet	RSSI-based Ellipse Model	Clustering Framework	Energy-Efficient Deterministic Approach
Detection Accuracy (%)	97.5	95.2	93.8	92.4
Energy Consumption (J/node)	10.8	12.3	11.9	13.1
Repair Time (seconds)	18	20	19	21
Coverage Improvement (%)	98.6	97.3	96.5	95.8

VI. DISCUSSION AND RESULT ANALYSIS

- **Detection Accuracy**

The detection accuracy rate of Deep CoverageNet reached 97.5% which surpassed the performance of RSSI-based Ellipse Model at 95.2% and Clustering Framework at 93.8%. Spatial features get extracted through CNNs and Transformers handle the temporal aspects due to their integration in a unified hybrid framework. The algorithm produced better detection accuracy through its precise coverage hole detection method especially in complex locations with obstacles.

- **Energy Consumption**

Reinforcement learning with energy-aware optimization in Deep CoverageNet lowers power consumption to a node-level rate of 10.8 J making it efficient by 12% relative to traditional deterministic models operating at 13.1 J. The system accomplished this through two strategies: first by directing mobile nodes to operate from energy-rich areas and second by designing efficient routes between nodes which reduced waste of energy during hole repair.

- **Repair Time**

Deep CoverageNet completed hole repairs within 18 seconds whereas the RSSI-based Ellipse Model required 20 seconds and Clustering Framework needed 19 seconds. Multiple reinforcement learning agents within Deep CoverageNet made immediate adjustments through feedback mechanisms to speed up their mobile node movements toward coverage holes.

The reported 18 seconds repair time is a consequence of the nodes' mobility. In the simulation, it was assumed that mobile nodes have a constant speed of 2.0 m/s. This time accounts for the time taken for the reinforcement learning agent to compute the optimal position to move to, and the physical movement of the node to the hole's centre. In addition, the energy spent for the displacement is accounted for in the 10.8 J/node calculation, and guarantees that the repair process is compliant with the physical and energy limitations in WSN.

- **Coverage Improvement**
  The coverage improvement achieved by Deep CoverageNet reached 98.6% which exceeded alternative methods by 1–3%. The algorithm succeeded at achieving almost 100% coverage because it identified tiny holes in the grid then placed nodes optimally to expand the sensing area with minimal duplicate coverage.

VII. Conclusions and Future Works

Deep CoverageNet proves its capability to both identify and fix coverage gaps in wireless sensor networks through its proposed algorithm. The deep learning framework which unites CNNs with Transformers enables the algorithm to detect with high precision while reducing energy usage and repair intervals. The simulation results demonstrate Deep CoverageNet excels better than standard RSSI-based models and clustering frameworks because of its minimal advantages in performance. The improved functionality of Deep CoverageNet enables it to function effectively as a scalable solution for dynamic environments especially disaster management systems and smart city monitoring applications.

Multiple obstacles continue to exist despite the technique's positive performance. The algorithm requires additional evaluation for its performance in massive-scale network conditions and extremely severe environmental interference conditions. The integration of federated learning techniques will improve how the solution functions within decentralized network environments. The upcoming development will employ the algorithm to three-dimensional environments alongside edge computing implementation for real-time applications. The future research on wireless sensor networks will benefit from utilizing blockchain security for data transfer and reinforcement learning optimization of multi-agent teamwork. Future developments will help Deep CoverageNet tackle new WSN challenges while keeping up a high level of efficiency and scalability.

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