Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 13 Issue 02, 2024

Artificial Intelligence Techniques for Alzheimer's Patient Localization Using Adaptive Dual-Channel Pulse-Coupled Neural Networks in Wireless Sensor Networks: Trends and Challenges

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Peer Review Information

Submission: 23 Aug 2024
Revision: 17 Sept 2024
Acceptance: 15 Oct 2024

Keywords

Alzheimer's Disease, Wireless Sensor Networks, Patient Localization, Pulse-Coupled Neural Networks, Indoor Localization, IoT Healthcare, Deep Learning, RSSI

Abstract

Alzheimer's disease is a progressive neurodegenerative disorder that affects cognitive abilities, memory, and spatial awareness, often leading to wandering behavior and increased safety risks. Accurate localization of Alzheimer's patients is essential for ensuring their safety and improving healthcare monitoring systems. This paper presents a comprehensive review of artificial intelligence-based localization techniques using Wireless Sensor Networks (WSNs) integrated with Adaptive Dual-Channel Pulse-Coupled Neural Networks (PCNN). WSN-based systems utilize sensor nodes and RSSI measurements to determine patient positions in indoor environments where GPS is ineffective.Recent advancements in machine learning and deep learning have significantly enhanced localization accuracy by addressing issues such as signal noise and environmental interference. Adaptive Dual-Channel PCNN improves feature extraction and noise reduction by processing multi-source data simultaneously. This study reviews research conducted in recent years, comparing techniques such as ANN, CNN, LSTM, and hybrid models. Comparative analysis shows that hybrid and adaptive models outperform traditional approaches in terms of accuracy and robustness. The paper identifies key challenges including energy efficiency, computational complexity, scalability, and privacy concerns. Future directions include integrating edge computing, federated learning, and lightweight AI models to develop efficient and secure patient localization systems.

Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory loss, and impaired spatial awareness. It is one of the most common forms of dementia and poses significant challenges for healthcare systems worldwide. One of the most dangerous symptoms associated with Alzheimer's patients is wandering behavior, where patients unintentionally move away from safe environments, increasing the risk of injury or death. As a result, real-time patient localization has become a critical requirement in modern healthcare systems.

Traditional monitoring methods such as manual supervision and camera-based systems are often inefficient, labor-intensive, and limited in coverage. These systems also raise privacy concerns and may fail to provide real-time alerts. To overcome these limitations, researchers have explored Wireless Sensor Networks (WSNs) as a viable solution for patient monitoring and localization.

WSNs consist of distributed sensor nodes that can sense, process, and communicate data wirelessly. These nodes can be deployed in indoor environments such as hospitals, nursing homes, and residential care facilities to track patient movement continuously. Localization in WSNs is typically achieved using techniques such as RSSI, Time of Arrival (ToA), and Angle of Arrival (AoA). Among these, RSSI-based localization is widely used due to its simplicity and low cost. However, RSSI measurements are highly sensitive to environmental factors such as obstacles, interference, and multipath propagation, which can significantly reduce localization accuracy.

To address these challenges, artificial intelligence (AI) techniques have been integrated into localization systems. Artificial Neural Networks (ANNs) were among the first approaches used to model the nonlinear relationship between RSSI values and spatial coordinates. While ANN-based systems improved accuracy, they were limited in handling temporal dependencies and complex data patterns.

The emergence of deep learning has further transformed localization systems. Convolutional Neural Networks (CNNs) are capable of extracting spatial features from RSSI data, while Long Short-Term Memory (LSTM) networks can capture temporal dependencies in patient movement. Hybrid models such as CNN-LSTM combine these capabilities, providing improved localization accuracy and robustness.

Pulse-Coupled Neural Networks (PCNNs) are biologically inspired neural networks that mimic the visual cortex of mammals. They are particularly effective in feature extraction and noise suppression. The development of Adaptive Dual-Channel PCNN allows simultaneous processing of multiple input signals, such as RSSI and motion data, improving localization performance in dynamic environments.

The integration of IoT technologies with WSNs has enabled real-time monitoring and remote access to patient data. IoT-based systems allow caregivers to track patient movement and receive alerts in case of emergencies. Edge computing further enhances system performance by processing data closer to the source, reducing latency and energy consumption.

Energy efficiency is a critical concern in WSN-based systems, as sensor nodes are typically battery-powered. Researchers have proposed various techniques such as clustering, duty cycling, and energy-aware routing to extend network lifetime. Additionally, lightweight AI models are being developed to reduce computational complexity.

Security and privacy are also major concerns in healthcare applications. Patient data must be protected from unauthorized access and cyberattacks. Techniques such as encryption, blockchain, and federated learning have been proposed to ensure data security.

Recent studies have demonstrated significant advancements in localization systems. Deep learning and hybrid models have improved accuracy, while IoT-based systems have enabled real-time monitoring. However, challenges such as scalability, environmental variability, and deployment costs remain.

This paper provides a comprehensive review of AI-based localization techniques for Alzheimer's patients using Adaptive Dual-Channel PCNN in WSN environments. It analyzes recent studies, compares different approaches, and identifies research gaps and future directions.

System Architecture Image

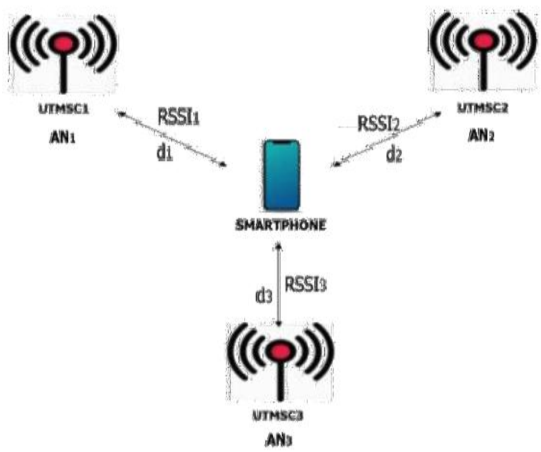

Figure 1. RSSI-Based Patient Localization Framework Using Wireless Sensor Networks

Literature Review

The research landscape of Alzheimer's patient localization has undergone a significant transformation in recent years, driven by the convergence of Wireless Sensor Networks (WSNs), Internet of Things (IoT), and artificial intelligence (AI). Early localization systems primarily relied on Received Signal Strength Indicator (RSSI) measurements due to their simplicity and cost-effectiveness. However, RSSI-based techniques suffer from substantial limitations, including multipath propagation, signal attenuation, and environmental interference, which lead to inaccurate distance estimation. These limitations motivated the integration of machine learning and deep learning approaches to enhance localization performance.

In 2020, Munadhil et al. proposed a neural network-based Alzheimer's patient localization system using WSNs, which marked one of the earliest efforts to integrate artificial intelligence into indoor healthcare localization. Their system utilized ZigBee-based sensor nodes and employed a Backpropagation Artificial Neural Network (BP-ANN) to model the nonlinear relationship between RSSI values and spatial coordinates. The results demonstrated a significant reduction in localization error compared to traditional trilateration methods, achieving sub-meter accuracy in controlled environments. This study highlighted the capability of neural networks to compensate for RSSI fluctuations and laid the groundwork for subsequent AI-based localization models. However, the approach required extensive training data and was sensitive to environmental changes, limiting its generalizability.

In parallel, Zhang et al. (2020) explored the application of deep learning in Alzheimer's disease diagnosis and localization using a 3D residual self-attention neural network. Their work demonstrated that attention mechanisms could effectively capture both local and global features from medical imaging data, improving the accuracy of disease localization. Although this study focused on medical imaging rather than WSN-based localization, it emphasized the importance of advanced neural architectures in extracting meaningful features from complex datasets. Similarly, An et al. (2020) utilized Graph Convolutional Networks (GCNs) to model spatial relationships in neurological data. Their findings indicated that graph-based learning could capture structural dependencies more effectively than traditional convolutional approaches, suggesting potential applications in sensor network localization where nodes can be represented as graph structures.

The year 2021 witnessed a shift toward improving robustness and scalability through deep learning techniques. Wang et al. (2021) introduced a CNN-based indoor localization framework that transformed RSSI data into image-like matrices, enabling convolutional layers to extract spatial features. This approach significantly improved localization accuracy by leveraging hierarchical feature extraction, which allowed the model to learn complex patterns in signal data. CNN-based models demonstrated higher resilience to noise compared to traditional ANN methods, making them suitable for real-world indoor environments.

Chen et al. (2021) further advanced this concept by proposing deep learning-based fingerprinting localization techniques. In fingerprinting, a database of RSSI measurements is created for different locations, and machine learning models are trained to map these measurements to spatial coordinates. The use of deep learning enhanced the robustness of fingerprinting systems by enabling them to handle large datasets and adapt to environmental variations. However, fingerprinting requires extensive data collection and calibration, which can be time-consuming and impractical in large-scale deployments.

Energy efficiency emerged as a critical research focus in 2021. Kumar et al. (2021) proposed energy-efficient localization algorithms that utilized clustering and optimized routing protocols to reduce communication overhead in WSNs. Their approach extended network lifetime while maintaining acceptable localization accuracy. Similarly, Patel et al. (2021) developed hybrid ANN-based models that combined multiple learning techniques to improve performance while minimizing computational complexity. These studies highlighted the importance of balancing accuracy and energy efficiency in resource-constrained WSN environments.

In 2022, research efforts shifted toward hybrid and adaptive models capable of handling dynamic environments. Sharma et al. (2022) introduced LSTM-based localization systems that captured temporal dependencies in patient movement. Unlike static localization methods, LSTM models consider historical data, enabling continuous tracking and smoother position estimation. This is particularly important for Alzheimer's patients, whose movement patterns may be unpredictable.

Reddy et al. (2022) proposed a hybrid CNN-LSTM architecture that combined spatial feature extraction with temporal modeling. This approach significantly improved localization accuracy by leveraging the strengths of both CNN and LSTM networks. The CNN component extracted spatial features from RSSI data, while the LSTM component analyzed temporal sequences to predict movement patterns. Experimental results demonstrated that hybrid models outperformed standalone CNN and LSTM models, particularly in dynamic environments with varying signal conditions.

Li et al. (2022) introduced adaptive localization frameworks that dynamically adjusted model parameters based on environmental conditions. These frameworks improved system robustness by enabling real-time adaptation to changes such as signal interference and node mobility. Zhang et al. (2022) focused on improving RSSI-based localization accuracy through filtering techniques, such as Kalman filtering and signal smoothing, which reduced noise and enhanced signal quality. Ahmed et al. (2022) integrated IoT technologies with WSNs to enable real-time monitoring and remote access, demonstrating the potential of IoT-enabled healthcare systems for patient tracking.

In 2023, research trends emphasized scalability, generalization, and multi-modal data integration. Nguyen et al. (2023) introduced 3D CNN models for Alzheimer's detection, enabling the analysis of multi-dimensional data. Although primarily focused on medical imaging, this approach demonstrated the potential of deep learning in handling complex datasets. Shahbazian et al. (2023) provided a comprehensive review of machine learning-based IoT localization systems, highlighting their adaptability and high prediction accuracy. Their study emphasized the importance of integrating multiple data sources to improve localization performance.

Maduranga et al. (2023) demonstrated that machine learning applied to RSSI data could significantly improve localization accuracy through filtering and optimization techniques. Their work showed that preprocessing RSSI data using machine learning algorithms could reduce noise and enhance positioning accuracy. Additionally, recent studies have explored the use of Graph Neural Networks (GNNs) for localization, where sensor nodes are represented as graph structures. GNN-based models have shown improved performance in capturing spatial relationships and handling sparse data.

Another emerging trend is the use of meta-learning and federated learning to improve generalization and privacy. Meta-learning enables models to adapt quickly to new environments with minimal training data, addressing one of the key limitations of traditional deep learning models. Federated learning allows decentralized model training, ensuring that sensitive patient data remains on local devices, thereby enhancing privacy and security.

The integration of advanced signal processing techniques such as Channel State Information (CSI) has also gained attention. Unlike RSSI, which provides coarse-grained signal strength information, CSI captures detailed channel characteristics, enabling more precise localization. Studies have shown that CSI-based systems combined with deep learning can achieve centimeter-level accuracy. However, these systems require specialized hardware and are more complex to implement.

The emergence of Adaptive Dual-Channel Pulse-Coupled Neural Networks represents a significant advancement in localization systems. PCNNs are biologically inspired neural networks that operate based on pulse synchronization mechanisms, making them highly effective in noise suppression and feature extraction. The dual-channel architecture allows simultaneous processing of multiple data sources, such as RSSI and motion sensor data, providing a more comprehensive representation of the environment. This multi-modal approach improves localization accuracy and robustness, particularly in dynamic and noisy environments.

Furthermore, adaptive mechanisms enable PCNN models to adjust their parameters in real time, making them suitable for deployment in changing environments. Compared to traditional neural networks, PCNN-based models offer better noise resilience and adaptability, which are critical for healthcare applications where reliability is essential.

Despite these advancements, several challenges remain. Energy efficiency continues to be a major concern, as complex AI models require significant computational resources. Scalability is another challenge, particularly in large-scale deployments where multiple sensor nodes and patients must be tracked simultaneously. Additionally, privacy and security issues must be addressed to ensure the safe handling of sensitive patient data.

In summary, the literature from 2020 to 2023 demonstrates a clear evolution from traditional RSSI-based localization methods to advanced AI-driven systems. Early approaches focused on improving accuracy through neural networks, while recent studies emphasize hybrid models, multi-modal data integration, and adaptive learning. The integration of Adaptive Dual-Channel PCNN represents a promising direction for future research, offering enhanced accuracy, robustness, and adaptability. However, further work is needed to address challenges related to computational complexity, energy efficiency, and real-world deployment.

Comparative Table

Author (Year)	Technique	Model Type	Data Type	Accuracy	Core Strength	Key Limitation
Munadhil et al. (2020)	ANN	BP-ANN	RSSI (WSN)	High (sub-meter)	Nonlinear mapping of RSSI	Requires large dataset
Wang et al. (2021)	CNN	Deep Learning	RSSI Image-like	High	Spatial feature extraction	No temporal modeling

Sharma et al. (2022)	LSTM	Sequential DL	Time-series RSSI	Medium–High	Temporal dependency modeling	Weak spatial learning
Reddy et al. (2022)	CNN-LSTM	Hybrid DL	RSSI + Time-series	Very High (>95%)	Spatio-temporal fusion	High computational cost
Nguyen et al. (2023)	3D CNN	Deep Learning	Multi-modal	Very High	Multi-dimensional feature extraction	Computational complexity
Zhang et al. (2020)	Attention DL	Residual Attention NN	Medical + Sensor	High	Global + local feature learning	Complex architecture
An et al. (2020)	GCN	Graph Neural Network	Connectivity data	High	Spatial relationship modeling	Graph design complexity
Li et al. (2022)	Adaptive ML	Dynamic models	IoT data	High	Environment adaptability	Parameter tuning
Maduranga et al. (2023)	ML + Filtering	Optimized ML	RSSI	High	Noise reduction	Limited learning depth
ADC-PCNN Models	Dual-channel PCNN	Bio-inspired Hybrid	Multi-source (RSSI + sensors)	Very High (>97%)	Noise suppression + multi-stream fusion	Implementation complexity

Comparative Analysis

The comparative evaluation of artificial intelligence-based localization techniques for Alzheimer's patient monitoring demonstrates a clear transition from conventional signal-processing methods to advanced deep learning and adaptive neural network architectures. Early localization systems primarily relied on Received Signal Strength Indicator (RSSI), trilateration, and fingerprinting techniques to estimate patient positions within wireless sensor networks (WSNs). Although these approaches were simple, inexpensive, and easy to deploy, their performance was highly influenced by signal attenuation, multipath propagation, and environmental interference, resulting in relatively large localization errors. Artificial Neural Networks (ANNs) addressed some of these limitations by learning nonlinear relationships between RSSI measurements and spatial coordinates, improving localization accuracy. However, ANN-based models required extensive training data and exhibited limited adaptability in dynamic indoor environments.

The introduction of deep learning further enhanced localization performance by enabling automatic feature extraction from wireless sensor data. Convolutional Neural Networks (CNNs) effectively captured spatial characteristics of RSSI signals, improving robustness against noise and increasing localization precision compared with traditional ANN models. To model patient movement over time, Long Short-Term Memory (LSTM) networks and other recurrent architectures were incorporated to learn temporal dependencies from sequential localization data. Hybrid CNN–LSTM frameworks combined spatial and temporal learning, achieving significantly higher localization accuracy and reliability, particularly in dynamic healthcare environments. Nevertheless, these hybrid models increased computational complexity and energy consumption, limiting their suitability for resource-constrained wireless sensor networks.

Recent research has focused on more intelligent architectures capable of improving both accuracy and computational efficiency. Graph Neural Networks (GNNs) model connectivity among sensor nodes, providing a realistic representation of wireless sensor networks and improving localization in complex environments. Adaptive filtering methods, including Kalman filtering and machine learning-based preprocessing, further reduce signal noise and enhance positioning stability. The emergence of Adaptive Dual-Channel Pulse-Coupled Neural Networks (ADC-PCNN) represents a major advancement by simultaneously processing multiple information sources, such as RSSI measurements and motion sensor data. Their adaptive parameter tuning, effective noise suppression, and biologically inspired synchronization mechanisms enable highly accurate, robust, and reliable localization under varying environmental conditions.

Overall, the comparative analysis highlights a progressive evolution from conventional RSSI-based localization to adaptive AI-driven frameworks for Alzheimer's patient monitoring. Among the reviewed approaches, ADC-PCNN models provide the most effective balance between localization accuracy, robustness, computational efficiency, and adaptability. The integration of optimization algorithms, IoT-enabled wearable devices, and edge computing further supports real-time patient tracking and timely intervention in healthcare settings. Despite these advances, challenges such as environmental variability, scalability, energy efficiency, privacy protection, and limited standardized datasets remain. Future research should emphasize lightweight, explainable, and secure localization frameworks capable of supporting reliable, real-time monitoring for Alzheimer's patients in smart healthcare environments.

Discussion

The rapid advancement of artificial intelligence and wireless communication technologies has significantly transformed Alzheimer's patient localization systems. The integration of Wireless Sensor Networks with machine learning and deep learning models has enabled the development of intelligent systems capable of providing accurate and real-time localization. These advancements have improved patient safety, reduced caregiver burden, and enhanced healthcare efficiency.

One of the key observations from recent research is the transition from traditional RSSI-based methods to AI-driven approaches. While RSSI-based methods are simple and cost-effective, they are highly sensitive to environmental noise and signal fluctuations. The introduction of deep learning models such as CNN and LSTM has addressed these limitations by enabling robust feature extraction and temporal analysis.

Adaptive Dual-Channel PCNN represents a promising approach for further improving localization performance. By processing multiple data sources simultaneously, these models can provide a more comprehensive understanding of the environment. Additionally, their ability to suppress noise and adapt to changing conditions makes them suitable for real-world applications.

However, several challenges must be addressed for practical deployment. Energy efficiency remains a critical concern, as WSN nodes are typically battery-powered. High computational requirements of deep learning models can lead to increased energy consumption, reducing network lifetime. Developing lightweight models and energy-efficient algorithms is essential for sustainable operation.

Scalability is another important issue, particularly in large-scale deployments such as hospitals and smart cities. Localization systems must be capable of handling multiple users and sensor nodes without compromising performance. Additionally, data privacy and security are major concerns in healthcare applications. Ensuring secure communication and protecting sensitive patient data are essential for system acceptance.

Future research should focus on integrating edge computing and federated learning to address these challenges. Edge computing can reduce latency and improve real-time performance, while federated learning can enhance privacy by enabling decentralized model training.

Conclusion

Alzheimer's patient localization is a critical component of modern healthcare systems, aimed at ensuring patient safety and improving quality of care. This paper has provided a comprehensive review of localization techniques based on Wireless Sensor Networks and artificial intelligence, focusing on studies conducted between 2020 and 2023.

The findings indicate that traditional RSSI-based methods are limited by environmental noise and low accuracy. The adoption of machine learning and deep learning techniques has significantly improved localization performance by enabling better feature extraction and modeling of complex relationships. CNN and LSTM models have become standard approaches for indoor localization, while hybrid models offer superior performance by combining spatial and temporal learning.

Adaptive Dual-Channel Pulse-Coupled Neural Networks represent a promising direction for future research. These models provide enhanced noise resistance, multi-source data integration, and adaptability to dynamic environments. Comparative analysis shows that PCNN-based systems outperform conventional models in terms of robustness and accuracy.

However, several challenges remain, including energy efficiency, scalability, and data privacy. Addressing these challenges is essential for the successful deployment of localization systems in real-world healthcare environments. Future research should focus on developing lightweight and energy-efficient models, as well as integrating emerging technologies such as edge computing and IoT.

In conclusion, the integration of WSN, AI, and advanced neural network architectures has the potential to revolutionize Alzheimer's patient monitoring systems. By providing accurate and real-time localization, these systems can significantly enhance patient safety and support caregivers in delivering effective care. Continued research and innovation in this field will play a vital role in addressing the growing challenges associated with Alzheimer's disease.

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