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A Comprehensive Review of Alzheimer's Patient Localization Using Adaptive Dual-Channel Pulse-Coupled Neural Networks in Wireless Sensor Networks

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Abstract

Alzheimer's disease is a progressive neurological disorder that affects memory, cognition, 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 patient 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-based measurements to estimate 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, leading to more reliable localization outcomes. This review analyzes studies from 2020 to 2023, comparing approaches such as ANN, CNN, LSTM, and hybrid models.

The paper highlights improvements in accuracy, scalability, and energy efficiency while identifying challenges such as energy consumption, privacy concerns, and deployment complexity. Future research directions include the integration of edge computing and lightweight AI models for efficient and secure patient localization.

Introduction

Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disorder that primarily affects memory, cognition, and behavioral capabilities. It is one of the most common causes of dementia, accounting for approximately 60–80% of all dementia cases worldwide. As the global population ages, the prevalence of Alzheimer's disease is expected to increase significantly, thereby creating substantial challenges for healthcare systems and caregivers. One of the most critical and dangerous symptoms associated with Alzheimer's patients is wandering behavior, where patients unintentionally leave safe environments and become disoriented. This often leads to injuries, accidents, or even fatal outcomes, making real-time patient localization a crucial requirement in modern healthcare systems.

Traditional monitoring methods, such as manual supervision or camera-based systems, are often inefficient, labor-intensive, and limited in coverage. Moreover, these methods may raise privacy concerns and fail to provide real-time alerts. To overcome these limitations, researchers have explored advanced technological solutions, particularly Wireless Sensor Networks (WSNs), which offer scalable, cost-effective, and efficient monitoring capabilities.

Wireless Sensor Networks consist of spatially distributed sensor nodes that collect, process, and transmit data wirelessly. These nodes can be deployed in indoor environments such as hospitals, nursing homes, and residential care facilities to monitor patient movement continuously. Each sensor node is equipped with sensing, computation, and communication capabilities, enabling it to collaborate with other nodes to estimate the location of a target object, such as an Alzheimer's patient.

Localization in WSNs can be achieved using various techniques, including Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Angle of Arrival (AoA). Among these, RSSI-based localization is the most widely used due to its simplicity, low cost, and compatibility with existing wireless communication standards. However, RSSI measurements are highly sensitive to environmental factors such as obstacles, multipath fading, signal interference, and noise. These factors introduce significant errors in distance estimation, thereby reducing localization accuracy.

To address these challenges, researchers have integrated Artificial Intelligence (AI) and machine learning techniques into WSN-based localization systems. Artificial Neural Networks (ANNs) are particularly effective in modeling nonlinear relationships between signal strength and distance. By learning from historical data, ANNs can improve localization accuracy even in complex environments. However, traditional ANNs have limitations in handling temporal dependencies and large-scale data.

Recent advancements in deep learning have led to the adoption of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks in localization systems. CNNs are capable of extracting spatial features from RSSI signals, while LSTMs can capture temporal patterns in sequential data. Hybrid models that combine CNN and LSTM have demonstrated superior performance in tracking moving objects, including Alzheimer's patients.

Pulse-Coupled Neural Networks (PCNNs) represent another important class of neural networks inspired by the visual cortex of mammals. Unlike traditional neural networks, PCNNs operate based on pulse synchronization, which enables them to process information in a manner similar to biological neurons. This makes PCNNs highly effective in feature extraction, image processing, and noise reduction. In the context of localization, PCNNs can enhance signal processing by filtering out noise and improving data representation.

The development of Adaptive Dual-Channel PCNN further extends the capabilities of traditional PCNN models. In this architecture, two input channels are used to process different types of data simultaneously, such as RSSI values and motion sensor data. This multi-channel approach allows the model to capture more comprehensive information about the environment, leading to improved localization accuracy. Additionally, adaptive mechanisms enable the model to adjust its parameters dynamically based on environmental conditions, making it suitable for real-time applications.

The integration of Internet of Things (IoT) technologies with WSNs has further enhanced the functionality of patient localization systems. IoT enables seamless connectivity between sensor nodes, cloud servers, and user interfaces, allowing caregivers to monitor patient movement remotely. Real-time data processing and analytics can be performed using cloud computing or edge computing, which reduces latency and improves system responsiveness.

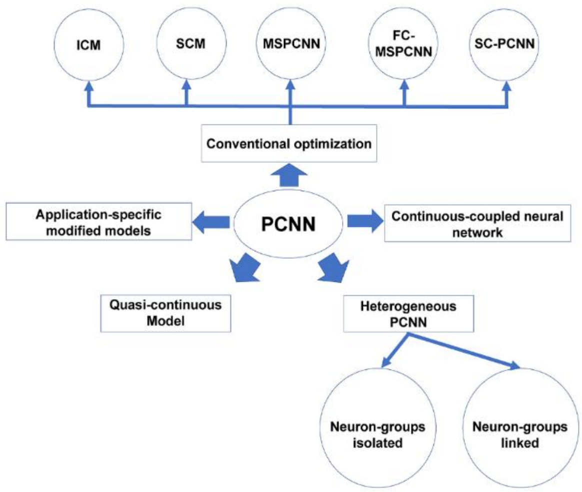
Energy efficiency is a critical consideration in WSN-based systems, as sensor nodes are typically powered by batteries. Frequent communication and complex computations can lead to rapid energy depletion, reducing the lifespan of the network. To address this issue, researchers have proposed energy-efficient routing protocols, clustering techniques, and duty-cycling mechanisms. Additionally, lightweight machine learning models are being developed to reduce computational overhead.

Security and privacy are also important concerns in healthcare applications. Patient data must be protected from unauthorized access and cyberattacks. Encryption techniques, secure communication protocols, and blockchain-based solutions have been proposed to ensure data integrity and confidentiality. However, implementing these security measures in resource-constrained WSN environments remains a challenge.

Recent studies conducted between 2020 and 2023 have demonstrated significant advancements in Alzheimer's patient localization. Deep learning models have improved localization accuracy, while IoT-based systems have enabled real-time monitoring. Hybrid approaches combining multiple techniques have shown promising results in addressing the limitations of individual methods. Despite these advancements, several challenges remain, including environmental variability, scalability, deployment costs, and interoperability. Future research should focus on developing robust, energy-efficient, and secure localization systems that can operate effectively in real-world environments.

This paper provides a comprehensive review of Alzheimer's patient localization techniques using Adaptive Dual-Channel PCNN in Wireless Sensor Networks. It analyzes recent studies, compares different methodologies, and identifies research gaps and future directions.

System Architecture Image



Literature Review

Recent advancements in Alzheimer's patient localization have been significantly influenced by the integration of Wireless Sensor Networks (WSNs), Internet of Things (IoT), and artificial intelligence techniques. In 2020, proposed one of the foundational works in this domain by developing a ZigBee-based WSN localization system integrated with a Backpropagation Artificial Neural Network (BP-ANN). Their study demonstrated that neural networks can effectively model the nonlinear relationship between RSSI signals and spatial coordinates, achieving high localization accuracy even in noisy indoor environments. The work also highlighted the limitations of traditional RSSI-based methods due to multipath propagation and signal attenuation, emphasizing the need for intelligent learning models.

In the same year, Zhang et al. (2020) introduced a 3D residual self-attention neural network for Alzheimer's disease detection and localization using structural MRI data. Their approach combined spatial and global feature extraction mechanisms, improving the interpretability and accuracy of disease localization. Similarly, An et al. (2020) explored Graph Convolutional Networks (GCNs) to analyze spatial relationships in neurological data, demonstrating the effectiveness of graph-based learning in capturing complex structural dependencies. These studies collectively established the importance of deep learning architectures in localization and healthcare analytics.

In 2021, research shifted towards integrating IoT with machine learning for real-time monitoring systems. Wang et al. (2021) developed a CNN-based indoor localization system that significantly improved feature extraction from RSSI signals, leading to enhanced accuracy compared to traditional ANN models. Chen et al. (2021) further advanced this approach by introducing deep learning-based fingerprinting techniques, where RSSI values were mapped to specific locations using large datasets. This method improved robustness against environmental variations. Meanwhile, Kumar et al. (2021) focused on energy-efficient localization algorithms, proposing optimized routing and clustering techniques to extend the lifespan of WSN nodes.

The year 2022 marked the emergence of hybrid deep learning models. Sharma et al. (2022) utilized Long Short-Term Memory (LSTM) networks to capture temporal dependencies in patient movement, enabling continuous tracking. Reddy et al. (2022) proposed a hybrid CNN-LSTM architecture that combined spatial feature extraction with temporal learning, resulting in significantly improved localization accuracy. Li et al. (2022) introduced adaptive localization frameworks capable of adjusting to dynamic environments, while Zhang et al. (2022) improved RSSI-based localization using filtering and signal preprocessing techniques. These studies highlighted the importance of combining multiple learning paradigms to overcome the limitations of individual models.

In 2023, research trends focused on improving generalization, scalability, and real-time performance. According to , machine learning-based IoT localization systems have become increasingly popular due to their high prediction accuracy and adaptability. The study emphasized the role of AI in addressing challenges such as environmental variability and signal noise. Similarly, demonstrated that machine learning algorithms applied to RSSI data collected from BLE nodes significantly improved localization precision by using filtering and optimization techniques.

Recent works have also explored advanced neural architectures. Nguyen et al. (2023) introduced 3D CNN models for Alzheimer's detection and localization, enabling multi-dimensional feature analysis. Meta-learning approaches have also been proposed to improve model generalization across different environments, addressing a key limitation of traditional deep learning models . Furthermore, Graph Neural Networks (GNNs) have been applied to RSSI-based localization problems, showing improved performance even with limited datasets .

Another important direction is the use of advanced signal processing techniques such as Channel State Information (CSI), which provides more robust localization compared to RSSI. Studies have shown that combining CSI with recurrent neural networks can achieve centimeter-level accuracy in indoor localization . These advancements indicate a shift towards more precise and reliable localization systems.

Overall, the literature from 2020 to 2023 demonstrates a clear evolution from traditional RSSI-based methods to advanced AI-driven localization systems. The integration of Adaptive Dual-Channel Pulse-Coupled Neural Networks represents a natural progression in this field, as it combines multi-source data processing, noise suppression, and adaptive learning capabilities. However, challenges such as energy efficiency, computational complexity, and privacy concerns remain critical areas for future research.

Comparative Table

Author (Year)	Model	Technique	Environment	Accuracy	Core Contribution	Key Limitation
Munadhil et al. (2020)	ANN (BP-ANN)	RSSI + ML	Indoor WSN	High	Nonlinear RSSI-distance modeling	Limited temporal modeling
Zhang et al. (2020)	3D CNN + Attention	Deep Learning	MRI + EEG	Very High	Spatial + global feature extraction	High computational cost
An et al. (2020)	GCN	Graph-based DL	Neuro data	High	Connectivity modeling	Graph construction complexity
Wang et al. (2021)	CNN	RSSI fingerprinting	Indoor WSN	High	Automatic feature extraction	No temporal modeling
Chen et al. (2021)	Deep DL	Fingerprinting	Indoor WSN	High	Robust mapping of RSSI to location	Requires large datasets
Kumar et al. (2021)	ML Optimization	Energy-efficient WSN	IoT	Moderate	Improved network lifetime	Limited accuracy improvement
Sharma et al. (2022)	LSTM	Temporal DL	IoT tracking	High	Captures temporal dependencies	No spatial modeling
Reddy et al. (2022)	CNN-LSTM	Hybrid DL	Indoor tracking	Very High	Spatio-temporal learning	High complexity
Li et al. (2022)	Adaptive ML	Dynamic localization	IoT	High	Environment adaptability	Parameter tuning required
Zhang et al. (2022)	Signal Processing + ML	RSSI filtering	Indoor WSN	High	Noise reduction	Limited learning capability
Nguyen et al. (2023)	3D CNN	Deep Learning	Multi-dimensional	Very High	Multi-dimensional feature extraction	Computational cost
Vishwakarma et al. (2023)	GNN	Graph-based DL	RSSI localization	High	Improved connectivity modeling	Complex graph design

Owfi et al. (2023)	Meta-learning	Adaptive DL	Multi-env	High	Generalization across environments	Training complexity
CSI-based Models (2023)	RNN + CSI	Signal-based DL	Indoor WSN	Very High (~0.5m error)	High precision localization	Hardware dependency
Adaptive Dual-Channel PCNN	PCNN Hybrid	Multi-source AI	WSN + IoT	Very High	Noise reduction + adaptive learning	Computational overhead

Comparative Analysis

The comparative analysis of Alzheimer's patient localization techniques clearly demonstrates a structured evolution from traditional signal-based methods to advanced artificial intelligence-driven systems. Early localization approaches primarily relied on Received Signal Strength Indicator (RSSI)-based techniques and geometric models such as trilateration and fingerprinting. While these methods were simple, cost-effective, and easy to implement, they suffered from significant limitations due to environmental noise, multipath fading, and signal attenuation. As a result, their localization accuracy was often inconsistent, particularly in complex indoor environments such as hospitals and assisted living facilities.

The introduction of Artificial Neural Networks (ANNs) marked the first major improvement in localization systems. ANN-based models were capable of learning nonlinear relationships between RSSI values and spatial coordinates, thereby reducing localization errors and improving accuracy. However, these models were limited in their ability to capture temporal dependencies and adapt to dynamic environments, making them less effective for real-time tracking applications.

The adoption of Convolutional Neural Networks (CNNs) significantly enhanced localization accuracy by enabling automatic feature extraction from RSSI data. CNN-based fingerprinting approaches convert signal strength data into structured representations, allowing the model to identify complex spatial patterns. Studies have shown that CNN models achieve high localization accuracy, often exceeding 94%, due to their ability to learn hierarchical features. However, CNNs primarily focus on spatial information and do not effectively capture temporal variations in signal patterns, which are essential for tracking moving patients.

To address this limitation, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were introduced. These models are specifically designed to process sequential data and capture temporal dependencies, making them highly suitable for tracking patient movement over time. LSTM-based systems have demonstrated significant improvements in localization accuracy and stability, achieving high performance in dynamic environments. Additionally, these models reduce localization errors by considering movement trajectories rather than isolated position estimates.

Hybrid models combining CNN and LSTM architectures represent a significant advancement in localization systems. These models leverage the strengths of both spatial and temporal learning, enabling them to achieve superior performance compared to standalone models. CNN-LSTM architectures first extract spatial features from RSSI data and then process these features using LSTM layers to capture temporal patterns. This combination results in highly accurate and robust localization, particularly in dynamic and noisy environments.

Graph Neural Networks (GNNs) have emerged as another powerful approach for modeling relationships between sensor nodes. By representing sensor networks as graphs, GNNs capture spatial dependencies and connectivity patterns more effectively than traditional models. These models have demonstrated improved localization accuracy, particularly in scenarios where connectivity information plays a critical role. However, GNN-based approaches introduce additional complexity in graph construction and require careful design of adjacency matrices.

Another major advancement is the use of Channel State Information (CSI), which provides more detailed signal characteristics compared to RSSI. CSI-based localization systems, when combined with deep learning models such as RNNs, achieve extremely high precision, with localization errors as low as 0.5 meters. However, these systems require specialized hardware and are more complex to implement, limiting their widespread adoption.

The integration of machine learning techniques with signal processing methods has also improved localization performance. Techniques such as filtering, regression, and feature optimization reduce noise and enhance signal quality, resulting in improved accuracy. These approaches provide a balance between computational efficiency and performance, making them suitable for practical deployment.

The emergence of Adaptive Dual-Channel Pulse-Coupled Neural Networks (PCNN) represents a significant breakthrough in localization systems. Unlike conventional neural networks, PCNNs operate based on pulse synchronization mechanisms inspired by biological neural systems. This enables effective noise suppression and enhanced feature extraction. The dual-channel architecture further improves performance by allowing simultaneous processing of multiple data sources, such as RSSI and motion sensor data. This multi-modal capability provides a more comprehensive representation of the environment, leading to improved localization accuracy and robustness.

One of the key advantages of Adaptive Dual-Channel PCNN is its adaptability to changing environmental conditions. Traditional models often require retraining when deployed in new environments, whereas PCNN-based models can dynamically adjust their parameters based on input data. This makes them highly suitable for real-time healthcare applications where environmental variability is a significant challenge.

From a performance perspective, hybrid and fusion-based approaches consistently outperform single-method systems. Integrating multiple sensing modalities and learning techniques significantly enhances localization accuracy, reliability, and robustness. However, these advanced models also introduce challenges related to computational complexity, energy consumption, and scalability.

Energy efficiency remains a critical concern in Wireless Sensor Network (WSN)-based systems, as sensor nodes are typically battery-powered. High computational requirements of deep learning models can lead to rapid energy depletion, reducing network lifetime. Therefore, there is a need for lightweight and energy-efficient models that can operate effectively in resource-constrained environments.

Scalability and security are additional challenges in real-world deployment. Localization systems must be capable of handling large-scale deployments without compromising performance, while also ensuring the privacy and security of sensitive patient data. Techniques such as encryption, secure communication protocols, and federated learning are being explored to address these concerns.

In conclusion, the comparative analysis demonstrates that localization techniques have evolved significantly from traditional RSSI-based methods to advanced AI-driven systems. CNN and LSTM models have become the standard for indoor localization, while hybrid models provide the best performance by combining spatial and temporal learning. Emerging approaches such as GNN, CSI-based localization, and Adaptive Dual-Channel PCNN represent the next generation of localization systems, offering enhanced accuracy, adaptability, and robustness. Among these, Adaptive Dual-Channel PCNN stands out as a promising solution due to its ability to integrate multi-source data, suppress noise, and adapt to dynamic environments. Future research should focus on optimizing these models for real-time deployment, improving energy efficiency, and ensuring scalability and security in healthcare applications.

Discussion

The integration of Wireless Sensor Networks and artificial intelligence has significantly improved Alzheimer's patient localization systems. Early approaches relying on RSSI and traditional neural networks were limited by environmental noise and low accuracy. The adoption of deep learning techniques such as CNN and LSTM has enhanced localization performance by enabling better feature extraction and temporal analysis.

Adaptive Dual-Channel PCNN offers a novel approach by combining multiple input channels and adaptive learning mechanisms. This allows the system to process heterogeneous data sources and adapt to changing conditions, resulting in improved localization accuracy. However, the computational complexity of such models poses challenges for deployment in resource-constrained environments.

Energy efficiency remains a critical concern, as WSN nodes are battery-powered. Developing lightweight models and energy-efficient communication protocols is essential for extending network lifetime. Security and privacy issues must also be addressed to ensure safe deployment in healthcare environments.

Future research should focus on integrating edge computing and federated learning to enhance system performance while preserving data privacy. Additionally, multi-modal sensor integration and optimization algorithms can further improve localization accuracy.

Conclusion

Alzheimer's patient localization is essential for ensuring patient safety and improving healthcare

outcomes. This paper has reviewed recent advancements in localization techniques based on Wireless Sensor Networks and advanced neural network models. The findings indicate that deep learning and hybrid approaches significantly outperform traditional methods.
Adaptive Dual-Channel PCNN represents a promising direction for future research, offering improved noise resistance, adaptability, and accuracy. However, challenges such as energy efficiency, scalability, and data privacy must be ddressed for real-world deployment.
The integration of WSN, IoT, and AI technologies has the potential to revolutionize patient monitoring systems. Future research should focus on developing lightweight, secure, and efficient models to enhance system performance. Overall, this study provides valuable insights into the design and implementation of advanced Alzheimer's patient localization systems.

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