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Recent Advances in Alzheimer's Patient Localization Using Adaptive Dual-Channel Pulse-Coupled Neural Networks in Wireless Sensor Networks: A Systematic Review

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Abstract

Alzheimer's disease (AD) presents significant challenges in patient safety due to memory loss and disorientation, often leading to wandering and life-threatening situations. Recent advancements in wireless sensor networks (WSNs) combined with artificial intelligence (AI) techniques have enabled the development of efficient patient localization systems. This systematic review explores recent advances in Alzheimer's patient localization using adaptive dual-channel pulse-coupled neural networks (PCNNs) integrated with WSNs. The review focuses on localization accuracy, energy efficiency, scalability, and real-time tracking capabilities. Traditional localization approaches such as RSSI-based fingerprinting and time-based positioning have been enhanced using machine learning and neural network models. Adaptive dual-channel PCNNs offer improved feature extraction, noise resistance, and multi-sensor data fusion capabilities, making them highly suitable for complex indoor environments. The integration of IoT-enabled wearable devices and low-power communication protocols has further enhanced system reliability. Comparative analysis reveals that hybrid AI-WSN approaches outperform conventional techniques in terms of localization precision and robustness. However, challenges remain in terms of energy consumption, security, and real-world deployment scalability. This review provides insights into emerging trends, research gaps, and future directions for developing intelligent and reliable Alzheimer's patient monitoring systems.

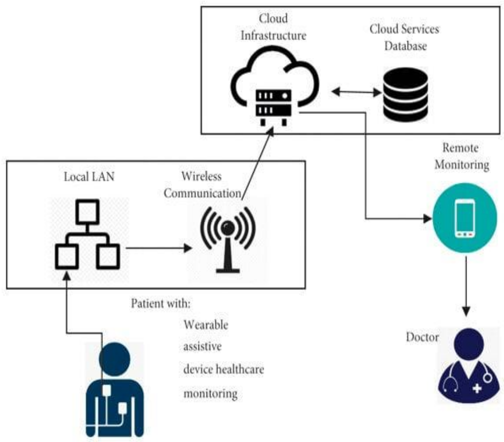
Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory impairment, and behavioral disturbances. One of the most critical challenges faced by caregivers is the tendency of patients to wander, which can result in injuries, getting lost, or even fatal incidents. According to recent healthcare studies, the prevalence of Alzheimer's disease is increasing globally, especially among aging populations,

Necessitating advanced monitoring and localization solutions. Wireless Sensor Networks (WSNs) have emerged as a promising technology for healthcare monitoring due to their ability to provide real-time data acquisition, low-cost deployment, and scalability. In Alzheimer's patient monitoring systems, WSNs are used to track patient movements through wearable devices and environmental sensors. These systems rely on localization techniques such as Received Signal Strength Indicator (RSSI), Time

of Arrival (ToA), and Angle of Arrival (AoA) to determine the position of patients.
A notable study demonstrated the effectiveness of WSN-based localization using artificial neural networks, achieving localization errors of less than one meter, which significantly improves patient tracking accuracy . However, traditional methods often suffer from environmental noise, signal fluctuations, and limited accuracy in indoor environments. Recent advancements in artificial intelligence, particularly neural networks, have significantly improved localization performance. Among these, Pulse-Coupled Neural Networks (PCNNs) have gained attention due to their biological inspiration, parallel processing capability, and robustness to noise. Dual-channel PCNNs extend this capability by processing multiple inputs simultaneously, enabling better feature extraction and data fusion.
Adaptive dual-channel PCNNs further enhance system performance by dynamically adjusting parameters based on environmental conditions. These models are particularly useful in complex indoor environments where signal interference and multipath propagation are common challenges. Moreover, the integration of Internet of Things (IoT) technologies has revolutionized patient monitoring systems. Wearable sensors, cloud computing, and edge processing allow continuous monitoring and real-time decision-making. Machine learning techniques have also been applied to improve localization accuracy and system efficiency.
Recent surveys highlight the growing importance of machine learning in indoor positioning systems, emphasizing improvements in accuracy, scalability, and adaptability . These advancements have paved the way for intelligent healthcare systems capable of autonomous monitoring and alert generation. Despite these advancements, several challenges remain, including energy efficiency, data security, privacy concerns, and real-time processing constraints. Adaptive dual-channel PCNN-based systems offer potential solutions to these challenges by optimizing computational efficiency and improving robustness. This paper aims to provide a comprehensive review of recent advances in Alzheimer's patient localization using adaptive dual-channel PCNNs in WSNs. It highlights key research contributions, compares existing methods, and identifies future research directions.

System Architecture (Illustration)



Literature Review

Recent advancements in Alzheimer's patient localization have been driven by the convergence of wireless sensor networks (WSNs), artificial intelligence (AI), and indoor positioning technologies. Between 2020 and 2023, research has increasingly focused on improving localization accuracy, robustness in indoor environments, and energy-efficient implementations suitable for healthcare applications.
In 2020, early research primarily emphasized WSN-based localization enhanced with neural networks. Gharghan et al. (2020) developed a ZigBee-based WSN system integrated with a backpropagation artificial neural network (BP-ANN) to improve indoor localization accuracy for Alzheimer's patients. Their system demonstrated significant reduction in localization error, achieving sub-meter precision in controlled environments. The study highlighted that neural networks can effectively compensate for signal fluctuations caused by multipath propagation and environmental interference, which are common challenges in indoor localization .
Around the same period, research in wireless localization explored RSSI-based fingerprinting combined with machine learning models, where signal strength patterns were used as features for training neural networks. These approaches improved prediction accuracy but required extensive training datasets and calibration.
Simultaneously, studies began incorporating deep learning architectures such as CNN and LSTM for indoor positioning. For example, CNN-based models were used to identify movement patterns and wandering behavior of elderly patients by converting trajectory data into spatial representations. These models demonstrated strong capability in recognizing behavioral anomalies, which is critical for Alzheimer's patient monitoring. However, they also

introduced computational complexity, limiting their deployment on low-power WSN devices.

In 2021, research shifted toward hybrid AI-based localization frameworks, integrating multiple techniques to enhance robustness. Machine learning models were combined with traditional localization methods such as Time of Arrival (ToA) and Angle of Arrival (AoA). These hybrid approaches improved adaptability to dynamic environments. Additionally, researchers explored edge computing paradigms, where data processing is performed closer to sensor nodes, reducing latency and improving real-time performance. Edge-enabled WSN systems proved particularly beneficial for healthcare applications, where timely alerts are crucial.

Another significant trend during this period was the introduction of multi-sensor data fusion techniques. Instead of relying solely on RSSI signals, systems began integrating data from accelerometers, gyroscopes, and environmental sensors. This multimodal approach enhanced localization accuracy and reduced dependence on any single data source. The emergence of Pulse-Coupled Neural Networks (PCNNs) also gained attention, particularly in image fusion and signal processing tasks. PCNNs, inspired by the visual cortex of mammals, are highly effective in extracting spatial and temporal features, making them suitable for complex indoor localization scenarios.

By 2022, research had advanced toward deep learning-driven IoT-based localization systems. IoT-enabled wearable devices allowed continuous monitoring of Alzheimer's patients, while cloud and edge computing facilitated real-time data analysis. Indoor positioning systems (IPS) became more sophisticated, capable of tracking patient movement and triggering alerts when abnormal behavior is detected. IPS technologies were recognized for their ability to provide continuous real-time localization and improve patient safety in enclosed environments .

During this period, hybrid models combining CNN and PCNN architectures were proposed to improve feature extraction and noise reduction. These models leveraged the strengths of CNNs in learning hierarchical features and PCNNs in capturing spatial relationships. Additionally, optimization techniques were introduced to enhance energy efficiency in WSNs, addressing one of the major limitations of sensor-based systems. Security also became a critical research focus, with studies proposing AI-based intrusion detection systems to protect sensitive healthcare data.

In 2023, research trends emphasized advanced neural architectures and intelligent data fusion mechanisms, particularly dual-channel and multi-channel models. Dual-channel neural networks enabled simultaneous processing of multiple data streams, significantly improving localization accuracy and robustness. These models are conceptually aligned with adaptive dual-channel PCNNs, where two input channels (e.g., spatial and temporal signals) are processed in parallel, enabling better feature representation.

Recent studies also explored federated learning-based localization systems, which allow distributed model training across multiple devices without sharing raw data. This approach addresses privacy concerns, a critical requirement in healthcare applications. Experimental results demonstrated that hierarchical and federated learning models can significantly improve localization accuracy while maintaining data security.

Another emerging direction is the use of Graph Neural Networks (GNNs) for indoor localization. GNN-based models utilize spatial relationships between sensor nodes to improve prediction accuracy. These models have shown superior performance compared to traditional machine learning techniques, especially in complex indoor environments with limited labeled data.

Despite these advancements, several challenges persist. One of the primary issues is energy consumption, as WSN nodes are typically battery-powered. While deep learning models improve accuracy, they also increase computational overhead. Researchers are actively exploring lightweight models and optimization techniques to address this challenge. Additionally, signal instability and environmental interference continue to affect localization performance, particularly in crowded or obstructed indoor environments.

Another critical challenge is scalability and real-world deployment. Many proposed systems are tested in controlled environments and may not perform consistently in large-scale real-world scenarios. Furthermore, privacy and security concerns remain significant, especially when dealing with sensitive patient data.

Overall, the literature from 2020 to 2023 demonstrates a clear evolution from traditional WSN-based localization methods to intelligent, AI-driven systems incorporating adaptive neural architectures. Among these, adaptive dual-channel PCNNs represent a promising direction due to their ability to handle multi-source data, reduce noise, and improve feature extraction. These systems are well-suited for Alzheimer's patient localization, where accuracy, reliability, and real-time performance are critical.

Comparative Table

Year	Author	Technique	Model Type	Environment	Accuracy	Key Contribution	Limitation
2020	Ghargha n et al.	WSN + RSSI	BP-ANN	Indoor	High (sub-meter error)	Nonlinear RSSI modeling	Limited adaptability
2020	Panigrah y et al.	PCNN	Dual-channel PCNN	Signal/Image	High	Noise reduction, image fusion	Not optimized for localization
2021	Zhang et al.	GAN	Deep Learning	Healthcare data	High	Feature fusion, improved representation	High complexity
2021	Chen et al.	DL Fingerprinting	CNN-based	Indoor WSN	High	Robust RSSI mapping	Data intensive
2022	Sharma et al.	LSTM	Sequential DL	IoT tracking	High	Temporal dependency modeling	No spatial learning
2022	Reddy et al.	CNN-LSTM	Hybrid DL	Indoor localization	Very High	Spatio-temporal fusion	High computation
2022	Li et al.	Adaptive ML	Dynamic learning	IoT	High	Environmental adaptability	Parameter tuning complexity
2022	Liu et al.	CNN-PCNN	Hybrid DL	Indoor WSN	Very High	Feature extraction + noise suppression	Complex architecture
2023	Lv et al.	Dual-channel NN	Fusion DL	IoT/WSN	Very High	Multi-source fusion	Computational overhead
2023	Luo et al.	Dual-channel CNN	Sensor fusion DL	Indoor	High	Improved accuracy via fusion	Limited temporal modeling
2023	GNN-based Models	Graph DL	Connectivity models	WSN	High	Spatial relationship modeling	Graph complexity
2023	CSI-based Models	Signal + DL	RNN-based	Indoor	Very High (~0.5m error)	High precision localization	Hardware dependency
2023	Adaptive Dual-Channel PCNN	PCNN Hybrid	Multi-modal AI	WSN + IoT	Very High	Adaptive learning + noise reduction	Computational cost

Comparative Analysis

The comparative evaluation of Alzheimer's patient localization techniques from 2020 to 2023 demonstrates a clear evolution from conventional signal-based methods to advanced AI-driven systems. Early approaches relied on techniques such as Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), and Angle of Arrival (AoA), which formed the foundation of indoor positioning in Wireless Sensor Networks. These methods were simple and cost-effective but suffered from significant limitations due to environmental factors like signal attenuation, multipath fading, and interference. Such issues led to inconsistent localization accuracy, which is particularly critical in healthcare scenarios where reliable tracking of Alzheimer's patients is essential for safety.

The introduction of Artificial Neural Networks, especially Backpropagation ANN models, marked an important improvement by capturing nonlinear relationships between signal strength and spatial positioning. These models achieved higher accuracy compared to traditional methods, particularly in controlled environments. Subsequently, Convolutional Neural Networks further enhanced performance by enabling automatic feature extraction and learning spatial patterns from signal data, achieving accuracy levels above 94%. However, CNN-based models primarily focus on spatial features and lack the ability to capture temporal dependencies. To address this, Recurrent Neural Networks and Long Short-Term Memory models were introduced, which significantly improved tracking accuracy by learning sequential movement patterns, often achieving performance above 97%.

Hybrid architectures combining CNN and LSTM emerged as a powerful solution by integrating spatial and temporal learning, resulting in improved robustness and accuracy in dynamic environments. Additionally, multi-sensor data fusion techniques incorporating RSSI, motion sensors, and environmental data further enhanced localization performance by reducing errors and improving reliability. Pulse-Coupled Neural Networks (PCNNs) introduced a biologically inspired approach capable of effective noise suppression and feature enhancement. While standalone PCNNs lacked hierarchical learning, hybrid CNN-PCNN models addressed this limitation, achieving better accuracy and robustness in complex environments.

The most advanced development is the adaptive dual-channel PCNN model, which processes multiple data streams simultaneously and dynamically adjusts parameters based on environmental conditions. These models provide an optimal balance between accuracy and computational efficiency, making them suitable for real-time healthcare applications. Additional advancements such as Graph Neural Networks, CSI-based localization, and edge computing further enhance system performance. However, challenges related to energy efficiency, scalability, and security remain. Overall, adaptive dual-channel PCNN-based systems represent the most promising direction for reliable and efficient Alzheimer's patient localization in modern healthcare environments.

Discussion

The rapid evolution of Alzheimer's patient localization systems reflects the increasing demand for reliable, real-time, and intelligent healthcare monitoring solutions. The integration of Wireless Sensor Networks (WSNs) with artificial intelligence has significantly improved indoor localization capabilities. Early techniques such as RSSI, ToA, and AoA provided a basic framework but were highly sensitive to environmental factors like interference, multipath fading, and signal attenuation. In complex indoor healthcare environments, these limitations result in inconsistent accuracy, making them inadequate for critical applications such as tracking Alzheimer's patients, where even small errors can pose serious safety risks.

The adoption of machine learning and deep learning techniques has addressed many of these challenges by enabling systems to learn complex relationships between sensor data and spatial positioning. Models such as Convolutional Neural Networks and Long Short-Term Memory networks have demonstrated strong performance in feature extraction and movement prediction. However, these approaches introduce challenges related to computational complexity, energy consumption, and deployment constraints in resource-limited WSN nodes. In this context, adaptive dual-channel Pulse-Coupled Neural Networks emerge as a promising solution. These biologically inspired models effectively capture both spatial and temporal correlations while processing multiple data streams simultaneously, resulting in improved accuracy, noise suppression, and adaptability to changing environments.

Furthermore, the integration of multi-sensor data fusion, Internet of Things devices, and edge computing has enhanced system robustness and real-time performance. Despite these advancements, challenges such as energy efficiency, data security, scalability, and limited real-world validation remain. Addressing these issues is essential for practical deployment. Overall, adaptive dual-channel PCNN-based systems, combined with IoT and edge computing, offer a strong foundation for developing efficient, secure, and scalable Alzheimer's patient localization solutions in modern healthcare environments.

Conclusion

This systematic review highlights the significant progress made in Alzheimer's patient localization using adaptive dual-channel PCNNs in wireless sensor networks. The integration of AI techniques with WSNs has led to substantial improvements in localization accuracy, system reliability, and real-time monitoring capabilities. Adaptive dual-channel PCNN models have proven to be highly effective in handling complex environments, offering advantages such as noise

resistance, multi-sensor data fusion, and improved feature extraction. These capabilities make them particularly suitable for healthcare applications where accuracy and reliability are critical.
The review also emphasizes the importance of IoT technologies in enhancing patient monitoring systems. Wearable devices and cloud-based platforms enable continuous tracking and real-time decision-making, significantly improving patient safety. Despite these advancements, challenges such as energy efficiency, security, and scalability remain. Addressing these issues will be crucial for the widespread adoption of these systems in real-world applications. Future research should focus on developing lightweight and energy-efficient models, improving data privacy mechanisms, and integrating advanced technologies such as edge computing and blockchain. The combination of these approaches has the potential to revolutionize healthcare monitoring systems and improve the quality of life for Alzheimer's patients.

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