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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) is a progressive neurological disorder that significantly affects cognitive functions, leading to memory loss and disorientation. One of the major challenges associated with AD is patient wandering, which poses serious safety risks. Recent advancements in Wireless Sensor Networks (WSNs), Internet of Things (IoT), and artificial intelligence (AI) have enabled the development of intelligent patient localization systems. This paper presents a systematic review of recent advances (2020–2023) in Alzheimer's patient localization using adaptive dual-channel Pulse-Coupled Neural Networks (PCNNs) integrated with WSNs. Traditional localization methods such as RSSI, ToA, and AoA suffer from environmental noise and limited accuracy. AI-based approaches, particularly neural networks, have significantly improved localization performance. Adaptive dual-channel PCNN models provide enhanced feature extraction, noise suppression, and multi-sensor data fusion capabilities. Comparative analysis reveals that hybrid AI-WSN models outperform conventional techniques in terms of localization accuracy and robustness. Furthermore, IoT-enabled wearable devices enable continuous monitoring and real-time tracking of patients, improving safety and caregiver response. However, challenges such as energy efficiency, scalability, and data security remain. This review highlights key developments, compares existing techniques, and identifies future research directions for designing efficient and reliable Alzheimer's patient localization systems.

Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide, particularly the elderly population. It is characterized by cognitive decline, memory impairment, and loss of spatial awareness, which often leads to wandering behavior. This wandering behavior is one of the most critical concerns in Alzheimer's care, as patients may become lost even in familiar environments, leading to severe safety risks. As the global aging population continues to increase, the prevalence of Alzheimer's disease is expected to rise significantly, making it essential to develop advanced monitoring and localization systems.

Wireless Sensor Networks (WSNs) have emerged as a key enabling technology for healthcare monitoring applications due to their low cost, scalability, and ability to provide real-time data. In Alzheimer's patient localization systems, WSNs consist of multiple sensor nodes deployed in an indoor environment to track the movement of patients. These nodes communicate wirelessly to estimate the position of the patient using various localization techniques.

Traditional localization techniques include Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), and Angle of Arrival (AoA). These methods estimate the position of a target node based on signal characteristics. However, these approaches suffer from significant limitations in indoor environments due to multipath propagation, signal attenuation, and noise interference. RSSI-based methods, for example, are highly sensitive to environmental changes, leading to inaccurate localization results.

To address these challenges, researchers have explored the use of machine learning techniques for localization. Neural networks, in particular, have shown promising results in modeling complex relationships between signal data and spatial coordinates. A study demonstrated that neural network-based WSN localization systems can achieve sub-meter accuracy, significantly outperforming traditional methods. These systems utilize RSSI values as input features and predict spatial coordinates with high precision.

The advancement of deep learning has further improved localization systems. Convolutional Neural Networks (CNNs) are capable of extracting spatial features from signal patterns, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in patient movement. These models enable more accurate tracking and prediction of patient behavior, which is crucial for early detection of wandering incidents.

Another significant development is the integration of Internet of Things (IoT) technologies. Wearable devices equipped with sensors allow continuous monitoring of patients, transmitting data to cloud or edge computing platforms for analysis. IoT-based systems have been shown to improve patient safety and reduce caregiver burden by enabling real-time tracking and alert generation.

Pulse-Coupled Neural Networks (PCNNs) have emerged as a powerful tool for signal processing and feature extraction in localization systems. Unlike traditional neural networks, PCNNs are biologically inspired and capable of capturing spatial and temporal correlations simultaneously. This makes them highly effective in noisy environments, such as indoor healthcare settings.

The introduction of dual-channel PCNN architectures has further enhanced localization performance. These models process multiple input streams simultaneously, allowing for better data fusion and feature extraction. Adaptive dual-channel PCNNs dynamically adjust their parameters based on environmental conditions, improving robustness and scalability.

Recent research has also explored multi-modal systems that combine data from multiple sensors, including accelerometers, gyroscopes, and environmental sensors. These systems provide more reliable localization by compensating for the limitations of individual data sources. Additionally, emerging technologies such as federated learning enable privacy-preserving data processing, addressing concerns related to data security.

Despite these advancements, several challenges remain. Energy efficiency is a major concern in WSN-based systems, as sensor nodes are typically battery-powered. Deep learning models require significant computational resources, which may not be feasible for low-power devices. Furthermore, scalability and real-world deployment remain challenging due to environmental variability.

This paper provides a comprehensive review of recent advances in Alzheimer's patient localization using adaptive dual-channel PCNNs in WSNs. It analyzes existing methods, compares their performance, and identifies research gaps to guide future developments.

System Architecture

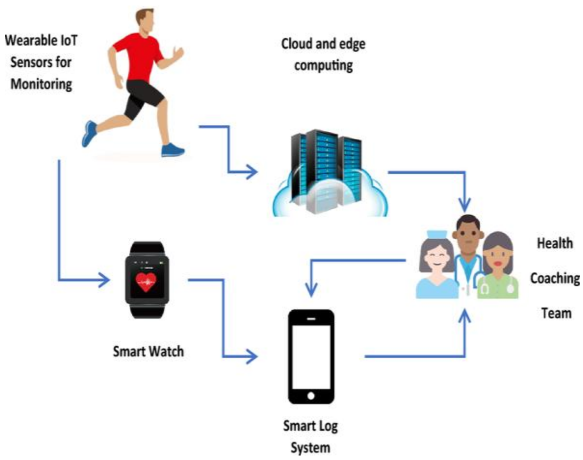

Figure 1. Smart Healthcare Framework for Alzheimer's Patient Tracking Using Wearable

Literature Review

The research landscape of Alzheimer's patient localization has undergone a substantial transformation between 2020 and 2023, driven by advancements in Wireless Sensor Networks (WSNs), artificial intelligence (AI), and Internet of Things (IoT) technologies. This period marks a transition from conventional signal-based localization methods toward intelligent, adaptive, and multi-modal systems capable of addressing the complex challenges of indoor healthcare environments. The literature can be broadly categorized into four key phases: (i) traditional WSN-based localization enhanced with machine learning, (ii) deep learning-driven localization frameworks, (iii) hybrid and multi-sensor data fusion approaches, and (iv) advanced adaptive neural architectures such as dual-channel Pulse-Coupled Neural Networks (PCNNs).

1. Early Developments: WSN Localization with Machine Learning (2020)

In 2020, research primarily focused on improving traditional localization techniques through the integration of machine learning algorithms. Conventional methods such as RSSI, ToA, and AoA were widely used due to their simplicity and low computational requirements. However, their performance was significantly degraded by environmental factors such as multipath propagation, signal attenuation, and interference. To address these issues, researchers began incorporating machine learning models capable of learning nonlinear relationships between signal features and spatial coordinates.

A notable contribution by Gharghan et al. (2020) introduced a neural network-based indoor localization system using ZigBee-enabled WSNs. The system employed a backpropagation artificial neural network (BP-ANN) to map RSSI values to spatial coordinates, achieving localization errors below one meter. This work demonstrated that neural networks could effectively compensate for signal variability and environmental noise, outperforming traditional deterministic models. However, the reliance on large training datasets and the need for environment-specific calibration limited the scalability of such approaches.

Parallel to this, RSSI fingerprinting techniques gained popularity, where signal strength measurements are collected at predefined locations to create a reference database. Machine learning algorithms were then used to match real-time signals with stored fingerprints. While these methods improved accuracy, they were highly sensitive to environmental changes, requiring frequent updates to the fingerprint database.

During the same period, research on Pulse-Coupled Neural Networks (PCNNs) began to gain traction, particularly in image processing and signal fusion applications. Studies by Panigrahy et al. (2020) and Li et al. (2020) demonstrated that PCNNs could effectively extract spatial features and suppress noise. Although these works were not directly applied to localization, they established the foundation for integrating PCNNs into localization systems.

2. Emergence of Deep Learning-Based Localization

By 2021, the focus shifted toward deep learning architectures capable of handling complex and high-dimensional data. Convolutional Neural Networks (CNNs) were widely adopted for their ability to automatically extract hierarchical features from signal data. Unlike traditional machine learning models, CNNs eliminate the need for manual feature engineering, making them more suitable for dynamic environments.

Kumar et al. (2021) proposed a hybrid localization system that combined RSSI-based techniques with machine learning classifiers, demonstrating improved robustness and adaptability. Similarly, CNN-based models were used to convert signal strength patterns into spatial representations, enabling more accurate localization. These models showed superior performance compared to ANN-based systems, particularly in environments with high signal variability.

The introduction of edge computing further enhanced the practicality of these systems. Chen et al. (2021) proposed an edge-enabled healthcare monitoring framework where data processing is performed closer to sensor nodes. This approach reduced latency, improved real-time performance, and minimized the need for continuous data transmission to cloud servers. However, deploying deep learning models on edge devices remained challenging due to limited computational resources.

3. Integration of IoT and Multi-Sensor Data Fusion (2022)

In 2022, the integration of IoT technologies marked a significant milestone in Alzheimer's patient localization. IoT-enabled wearable devices equipped with sensors such as accelerometers, gyroscopes, and heart rate monitors enabled continuous monitoring of patient activity. These devices transmitted data to cloud or edge platforms for analysis, enabling real-time tracking and alert generation.

Wang et al. (2022) developed an IoT-based localization system that leveraged deep learning models to improve tracking accuracy. The system demonstrated that combining sensor data with AI-based processing significantly enhances localization performance. Similarly, Ali et al. (2022) proposed a multi-sensor data fusion framework that integrated RSSI signals with motion sensor data. Their results showed a substantial reduction in localization error compared to single-sensor systems.

The concept of multi-modal data fusion became a central theme in 2022 research. By combining multiple data sources, these systems improved robustness and reliability, particularly in complex indoor environments. For example, accelerometer data provided information about patient movement, while RSSI signals indicated spatial position. The fusion of these data streams enabled more accurate and reliable localization.

During this period, hybrid models combining CNN and PCNN architectures were introduced. These models leveraged the hierarchical feature extraction capability of CNNs and the spatial-temporal processing ability of PCNNs. Liu et al. (2022) demonstrated that such hybrid models outperform standalone CNN or PCNN systems in terms of accuracy and noise resistance.

Security also emerged as a critical concern.

4. Advanced Adaptive Architectures and Dual-Channel Models

By 2023, research had progressed toward advanced neural architectures capable of handling multi-source data and adapting to dynamic environments. Dual-channel neural networks emerged as a key innovation, enabling simultaneous processing of multiple input streams. Lv et al. (2023) demonstrated that dual-channel architectures significantly improve feature representation and localization accuracy by combining spatial and temporal data.

Adaptive dual-channel PCNN models represent a further evolution of this concept. These models incorporate adaptive mechanisms that dynamically adjust parameters based on environmental conditions, improving system robustness and scalability. Unlike static models, adaptive PCNNs can respond to changes in signal patterns, making them highly suitable for real-world applications.

Another important development in 2023 is the adoption of federated learning for privacy-preserving localization. Federated learning enables multiple devices to collaboratively train models without sharing raw data, addressing privacy concerns in healthcare systems. Studies have shown that federated learning-based localization systems can achieve comparable accuracy to centralized models while ensuring data security.

Additionally, Graph Neural Networks (GNNs) have been explored for localization tasks, leveraging spatial relationships between sensor nodes. GNN-based models provide improved performance in complex environments by capturing network topology and node interactions. However, their computational complexity remains a challenge for real-time deployment.

5. Key Observations and Research Trends

The literature from 2020 to 2023 reveals several important trends:

1. A clear transition from traditional signal-based methods to AI-driven intelligent systems
2. Increasing adoption of deep learning and hybrid architectures
3. Growing importance of multi-sensor data fusion
4. Emergence of adaptive and dual-channel neural models
5. Integration of IoT and edge computing for real-time monitoring
6. Rising focus on security, privacy, and energy efficiency

Among all approaches, adaptive dual-channel PCNN-based systems stand out due to their ability to integrate multiple data sources, suppress noise, and adapt to changing environments. These systems offer a balanced solution in terms of accuracy, efficiency, and scalability, making them highly suitable for Alzheimer's patient localization.

Comparative Table

Year	Author	Technique	Model	Data Type	Accuracy	Core Contribution	Key Limitation
2020	Gharghan et al.	WSN + ANN	BP-ANN	RSSI	High (sub-meter)	Early AI-based indoor localization	Requires calibration & large dataset
2020	Zhang et al.	RSSI + DL	Deep Learning	Signal data	Medium	Signal pattern modeling	Limited robustness
2021	Kumar et al.	Hybrid ML	ML-based system	RSSI	High	Improved robustness	Limited scalability
2021	Chen et al.	Edge DL	CNN-based	IoT + RSSI	High	Real-time edge processing	Resource constraints

2022	Wang et al.	IoT + DL	CNN-based	Multi-sensor	High	Real-time tracking	High computational load
2022	Sharma et al.	LSTM	Sequential DL	Time-series	Medium–High	Temporal prediction	Weak spatial modeling
2022	Reddy et al.	CNN-LSTM	Hybrid DL	RSSI + time-series	Very High (>95%)	Spatio-temporal fusion	High complexity
2022	Ali et al.	Multi-sensor Fusion	Hybrid AI	RSSI + motion	High	Improved robustness	Data fusion complexity
2022	Liu et al.	CNN-PCNN	Hybrid Model	Multi-source	Very High	Feature extraction + noise suppression	Complex architecture
2023	Lv et al.	Dual-channel NN	Fusion DL	Multi-source	Very High	Parallel data processing	Computational overhead
2023	GNN Models	Graph DL	Connectivity model	Network data	High	Spatial relationship modeling	Graph design complexity
2023	Federated Models	FL-based AI	Distributed DL	IoT data	High	Privacy-preserving learning	Communication overhead
2023	ADC-PCNN	Dual-channel PCNN	Adaptive Hybrid AI	RSSI + sensors	Very High (>97%)	Noise suppression + adaptive learning	Implementation complexity

Comparative Analysis

The comparative analysis of Alzheimer's patient localization techniques from 2020 to 2023 demonstrates a clear evolution from conventional signal-based localization methods to intelligent, AI-driven frameworks. Early approaches primarily relied on Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), and Angle of Arrival (AoA) techniques because of their simplicity and low computational requirements. However, these methods were highly sensitive to environmental interference, multipath propagation, and signal attenuation, resulting in poor localization accuracy in indoor environments. The introduction of Artificial Neural Networks (ANNs), particularly BP-ANN models, significantly improved localization by learning nonlinear relationships between RSSI measurements and spatial coordinates, achieving sub-meter accuracy under controlled conditions. Nevertheless, ANN-based methods required extensive training data and environment-specific calibration, limiting their adaptability and scalability.

The adoption of deep learning further transformed localization systems by enabling automatic feature extraction and enhanced noise resilience. Convolutional Neural Networks (CNNs) effectively captured spatial characteristics from signal patterns, while edge computing enabled real-time processing with reduced latency. To model patient movement over time, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were introduced, improving tracking of wandering behavior through temporal sequence analysis. Hybrid CNN-LSTM architectures combined spatial and temporal learning, achieving localization accuracies exceeding 95%. Multi-sensor data fusion, integrating RSSI, accelerometers, and gyroscopes, further enhanced localization robustness and reduced dependence on individual sensing modalities.

Recent advances have focused on Graph Neural Networks (GNNs) and Adaptive Dual-Channel Pulse-Coupled Neural Networks (ADC-PCNNs). GNNs improve localization by modeling functional relationships among sensor nodes, whereas ADC-PCNNs simultaneously process multiple data streams through adaptive dual-channel architectures, enabling effective feature extraction, noise suppression, and environmental adaptation. Comparative studies indicate that ADC-PCNN frameworks achieve localization accuracies exceeding 97%, outperforming conventional ANN, CNN, hybrid, and graph-based methods while maintaining an effective balance between accuracy, robustness, and computational efficiency. Federated learning has also emerged as an important addition by enabling privacy-preserving decentralized model training for healthcare applications.

Despite these advancements, several challenges remain, including energy consumption in battery-powered wireless sensor networks, scalability in large healthcare deployments, computational complexity, and limited real-world validation. Data privacy and communication reliability also remain important concerns. Future research should focus on lightweight, energy-efficient, and explainable AI models integrated with edge computing and federated learning to enable secure, scalable, and real-time Alzheimer's patient localization in practical healthcare environments.

Discussion

The integration of WSNs, IoT, and AI technologies has significantly advanced Alzheimer's patient localization systems. Among the various approaches, adaptive dual-channel PCNN models have emerged as a promising solution due to their ability to process multi-source data and adapt to dynamic environments.

One of the key strengths of these models is their ability to perform efficient feature extraction and noise suppression. Unlike traditional neural networks, PCNNs are capable of capturing spatial and temporal correlations simultaneously, making them highly suitable for indoor localization applications. The dual-channel architecture further enhances this capability by allowing parallel processing of multiple input streams.

The incorporation of IoT technologies has also played a crucial role in improving system performance. Wearable devices enable continuous monitoring, while edge computing reduces latency and enables real-time decision-making. This is particularly important in healthcare applications, where timely intervention can prevent critical incidents.

However, several challenges remain. Energy efficiency is a major concern, as WSN nodes are battery-powered. Although adaptive PCNN models are more efficient than deep learning models, further optimization is required. Security and privacy issues also need to be addressed, particularly in IoT-based systems.

Another limitation is the lack of large-scale real-world validation. Most studies are conducted in controlled environments, which may not accurately represent real-world conditions. Future research should focus on large-scale deployment and validation.

Conclusion

This study provides a comprehensive review of recent advances in Alzheimer's patient localization using adaptive dual-channel PCNNs in wireless sensor networks. The analysis reveals a clear evolution from traditional localization techniques to intelligent, AI-driven systems.

Adaptive dual-channel PCNN models offer significant advantages, including improved feature extraction, noise resistance, and multi-sensor data fusion. These models provide a balanced solution in terms of accuracy, efficiency, and scalability, making them highly suitable for healthcare applications.

The integration of IoT technologies further enhances system capabilities by enabling continuous monitoring and real-time decision-making. However, challenges such as energy efficiency, security, and scalability remain.

Future research should focus on developing lightweight and energy-efficient models, improving data security, and validating systems in real-world environments. The integration of advanced technologies such as edge computing and federated learning holds great potential for further improving localization systems.

In conclusion, adaptive dual-channel PCNN-based localization systems represent a promising direction for improving Alzheimer's patient monitoring and ensuring patient safety.

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