Wireless Sensing of Gait for Neurodegenerative Disease Assessment: A Scoping Review

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Abstract

Early diagnosis of neurodegenerative diseases is a significant public health challenge, yet crucial for better prognoses. Gait analysis accomplishes this task by detecting abnormal motion or declining motor control, which are strong early indicators of neurodegeneration. A new healthcare paradigm, shifting from clinical settings to home-based approaches, promotes less intrusive and privacy-preserving monitoring solutions. In this context, wireless gait analysis methods, such as radars and commercial cameras, are well-suited for home-based neurodegenerative disease assessment. These non-contact sensing technologies offer a less cumbersome alternative to traditional methods while maintaining reliability. We conducted this scoping review study to examine wireless sensing solutions for gait analysis in neurodegeneration assessment. In accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Review (PRISMA-ScR) guidelines, searches were conducted on the Scopus, PubMed, IEEE, and ACM databases. 16 of 139 articles were included in this review, which were evaluated for sensor choices, gait features, means of analysis, and the investigated condition. Studies indicated that the RGB/depth cameras and radars were effective means of capturing real-time gait data. Step length and speed were found to be the most accurate discriminators among several gait parameters for data analysis in this study, regardless of the sensing approach chosen. Various descriptive statistical methods and data-driven models have been explored as the analytical tools for assessing neurodegeneration-affected gait. By evaluating various approaches to wireless sensing-based gait analysis in this scoping review, we discuss and highlight challenges and opportunities for future research.

CCS Concepts

• **Applied computing → Health care information systems**.

Keywords

Sensing, Neurodegeneration, Dementia, Biomarker, Phenotyping

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1 Introduction

The incidence of neurodegenerative diseases such as Alzheimer's and Parkinson's has increased at alarming rates worldwide [1]. The management of these diseases is more efficacious before the manifestation of overt symptoms [34]. Gait [7, 10, 23, 19] is a critical biomarker for assessing the progression of these diseases [31]. Sensing technologies that enable gait analysis at home, without the need for clinical visits, are essential for the effective and timely assessment and management of neurodegenerative diseases.

Wireless sensing [30, 17], owing to its noninvasive nature, emerges as a promising approach for longitudinal monitoring of gait patterns, enabling early diagnosis before clear symptoms of neurodegenerative diseases appear. In this paper, the term "wireless sensing" specifically refers to non-contact sensing technologies which do not require physical markers/tags or direct physical interaction with the subject or environment to detect and track objects or human movements. Previous work indicates that wireless sensing technologies, such as cameras and radio frequency (RF) technologies, provide an effective means for capturing and analyzing gait patterns [28, 13]. In addition, several previous reviews have found general agreement between wireless sensing technologies and gold-standard motion capture systems for gait analysis [28]. Such wireless sensing technologies offer a cost-efficient approach to providing actionable insights for daily health management, aligning with the ongoing shift from clinical-based to home-based healthcare. Therefore, it is important to have a comprehensive understanding of their potential effectiveness in assessing gait patterns for neurodegenerative diagnostics. However, to the authors' knowledge, no review study has systematically analyzed the use of wireless sensing methods [1] for this task, despite existing reviews on the use of wearable sensors for gait analysis in patients with ADRD or Parkinson's [21].

To fill the knowledge gap, we conducted this scoping review study to examine the principles and applications of wireless sensing solutions for gait analysis in neurodegenerative disease assessment. Specifically, we focus on analyzing the gait features and analytical models in the pipeline of wireless sensing-based gait analysis across related tasks.

Through this scoping review study, we find that gait analysis pipelines generally take one of two forms: explainable or end-to-end. RGB/depth camera-based pipelines are typically explainable as they produce clinically aligned gait parameters, so we are able

[1]While using the term "markerless" might seem more appropriate than "wireless" in the context of gait analysis, it fails to cover recent advancements in radio frequency (RF)-based sensing technologies, such as radar and WiFi. Therefore, we chose to use the term "wireless sensing".

Table 1: Search Queries.

Database	Query	Result Count
Scopus	TITLE-ABS (gait) AND TITLE-ABS (wireless) AND TITLE-ABS (sens*) AND (adrd OR alzheimer OR dementia OR parkinson) AND PUBYEAR > 2019	109
Pubmed	("gait"[Title/Abstract] AND "wireless"[Title/Abstract]) AND (sens*[Title/Abstract]) AND (adrd OR alzheimer OR dementia OR parkinson) from 1/1/2019	15
IEEE	("Abstract":gait) AND ("Abstract":wireless) AND ("Abstract":sens*) AND ("All Metadata":adrd OR "All Metadata":alzheimer OR "All Metadata":dementia OR "All Metadata":parkinson), 2019-2025	14
ACM	[Abstract: gait] AND [Abstract: wireless] AND [Abstract: sens*] AND [[All: adrd] OR [All: alzheimer] OR [All: dementia] OR [All: parkinson]] AND [E-Publication Date: (01/01/2019 TO *)]	1

to assess and compare the effectiveness of gait parameters in neurodegenerative diseases assessment. Based on the surveyed studies, gait speed and stride/step length are the most reliable indicators of neurodegenerative diseases. On the other hand, RF-based pipelines are often end-to-end in the sense that gait parameters are not directly available. Instead, they rely on data-driven approaches to map neurodegenerative diseases to RF features, such as micro-Doppler signatures. By evaluating the pipelines in surveyed studies, we highlight key challenges and opportunities for advancing wireless sensing-based gait analysis in neurodegenerative disease assessment.

2 Methods

We conduct this scoping review study in order to assess the state of wireless sensing-based gait analysis and suggest further research. The protocol was developed based on the Preferred Reporting Items for Systematic Reviews and Meta-analysis Protocols (PRISMA-P), specifically the PRISMA extension for scoping reviews published in 2018 [29].

Only peer-reviewed journal articles and conference proceedings were included in the review. The included articles must have used a wireless (namely non-contact, markerless) means of detection such as radar or a camera to analyze the walking gait of subjects in connection with neurodegenerative disorders. Papers were excluded if they were review articles, were not written in English, were published before 2020, included nonhuman participants, or if data were collected by other means, such as by a wearable suite of sensors. A flow chart showing the course of evaluation can be seen in Figure 1.

Search queries were developed by conducting an overview of articles. Keywords such as "wireless", "sens*", and "gait" proved most useful for narrowing the breadth of the search results. To identify relevant studies, searches were conducted in the Scopus, PubMed, IEEE Xplore, and ACM databases in January 2025. The specific search queries are displayed in Table 1. The raw searches were imported into Zotero, a reference management tool. This tool was used to eliminate duplicates and organize the abstracts for evaluation. A reviewer evaluated the titles, then abstracts, and finally the full text of all papers found by search queries. Ultimately, 16 papers were included in the final review. The data evaluated includes sample size, pathological focus, sensors used, specific focal gait characteristics, analytical models, and evaluated results. Based on the search queries executed, we identified studies focused on using wireless sensing of gait for the analysis of neurodegenerative diseases and its applications for the care and management of related conditions in a broader context.

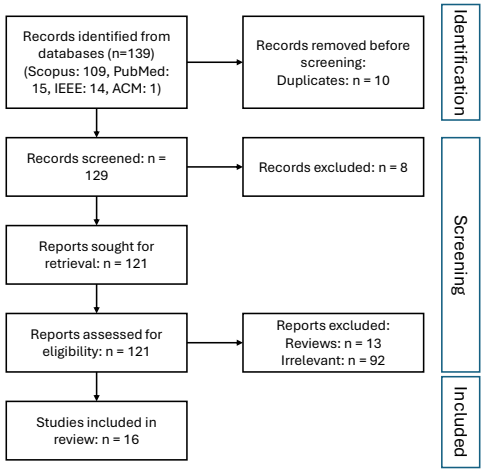


Figure 1: Literature search process based on PRISMA-ScR.

3 Results

After reviewing the articles, 16 of the initial 139 search results were evaluated in this study, and they are compiled in Table 2 and Table 3. Five of the 16 studies were focused on Parkinson's disease or related symptoms, while 6 focused on dementia or Alzheimer's disease. The remainder were more generally focused on identifying anomalous gait. Key findings from each study include 1) the pathological focus or application of gait analysis, 2) the gait features assessed, 3) the specific kind of wireless sensor used, 4) the means of analysis used on the obtained data, 5) the size of the dataset used, and 6) a summary of the reported results. Most of the studies reviewed had a small sample of participants, from which the researchers gathered episodes. More episodes were sometimes generated by data augmentation techniques. Participant counts ranged from 5 to 500. Two studies instead used pre-recorded videos from either the public domain or previous research.

3.1 Sensors

The current gold standard for measuring gait parameters without a wearable apparatus is a full motion capture system. However, these systems tend to be both unwieldy and expensive. Instead, the primary alternatives are RGB cameras, the Microsoft Kinect system (as a representative depth camera), and RF sensing systems (including ultra-wideband, mm-wave, micro-Doppler radars, and WiFi).

3.1.1 RGB Cameras. Four of the identified studies chose to use a smartphone camera or similar device for gait data collection [25, 6, 15, 11]. Cameras are both ubiquitous and sufficient for providing a

References	Focus of Tasks	Sensor	Gait Features	Analytical Method	Sample/Dataset	Result Summary
Rupprechter et al., 2021 [25]	Parkinson's	Camera	speed, arm swing, postural control, smoothness	Gamma-Poisson Bayesian model	729 videos	50 percent categorized performance with four categories
Connie et al., 2022 [6]	Parkinson's	Camera	posture, steadiness, arm swing, step height, step, cadence, speed	random forest	167 subjects (93 healthy and 74 with PD)	95% accuracy front view; 97% accuracy side view
Iseki et al., 2023 [15]	Parkinson's, Hydrocephalus	Camera	24 coordinates	light GBM	274 participants	71.9% AUROC
Eguchi et al., 2024 [11]	Parkinson's, spinocerebellar degeneration	Camera	25 joint locations	DNN	143 participants	83% accuracy between PD and SCD
Habib et al., 2024 [12]	Parkinson's	Wi-Fi	CSI data	LSTM	10 participants	98.66% binary classification performance
You et al, 2021 [31]	Alzheimer's	Kinect cameras	half-of-gait cycle/variation, stride length, speed, hand swing, head posture variation	LSTM	53 participants	88-92% accuracy classifying AD gait
Korhani et al., 2023 [3]	Dementia	Kinect cameras	step width, step time variability, estimated margin of stability, Parkinsonism score	SVM	54 participants	75% AUROC fall prediction
Ng et al., 2020 [22]	Dementia	Kinect cameras	cadence, symmetry	linear regression	31 participants	Cadence and average step width best predictors from multivariate regression ($p = 0.0001$ and $p = 0.00031$ respectively)
Zhang et al., 2021 [32]	Dementia	Kinect cameras	gait cycles	CNN, SVM	300 participants	74% sensitivity for dementia
Kondragunta et al., 2020 [16]	Dementia	Kinect cameras	step/stride time, step length, mean stride, cadence, velocity	classification comparison	20 participants	all gait parameters show significant differences, step length decrease from 25.9 to 19.8 after mild cognitive impairment
Ren et al., 2024 [24]	Dementia	Micro-Doppler radar	micro-Doppler signatures	CNN/transformer	137 participants 40 with dementia and 77 healthy	frequency domain better predictive power than time domain by 5.91
Seifallahi et al., 2021 [27]	Mild cognitive impairment	Kinect cameras	stride length, left/right step length, gait cycle	adaptive neuro-fuzzy inference system, LSTM, SVM	150 participants	ANFIS best, 93% accuracy

Table 2: Results of the evaluated studies focused on detection of neurodegenerative diseases.

Citation	Focus of Tasks	Sensor	Gait Features	Analytical Method	Sample/Dataset	Result Summary
Hadjipanayi et al., 2024 [13]	Gait parameter estimation	Ultra-wide band radar	step/stride time/length, cadence, walk ratio, walking speed, swing/stance/double-support time	Spearman correlation and Bland-Altman analysis	12 participants	90% similarity aside from double support phase
Chen et al., 2022 [5]	Fall prediction	Kinect cameras	hip joint flexion/extension angles, hip joint abduction/adduction, knee joint angle	SVM, KNN, CNN, LSTM	3 participants	SVM best at 94.9% accuracy
Abedi et al., 2023 [2]	Activity recognition	mmWave radar	speed, step length, step time	GRU model	85 participants	86% accuracy on untrained participants; 93% on trained participants
Hayashi et al., 2021 [14]	Classification of gait patterns between young and elder adults	Micro-Doppler radar	maximum, minimum velocity	LSTM	300 participants	95% accuracy classifying old vs young

Table 3: Results of the evaluated studies focused on gait analysis.

high-quality video stream. With advances in computer vision [4], joint locations can be extracted from 2D imaging data for gait analysis. However, collecting imagery data inevitably raises privacy concerns.

3.1.2 Depth Camera. Seven of sixteen identified studies used the Microsoft Kinect, a commercially available depth camera, as their means of acquiring gait data [31, 3, 22, 33, 18, 27, 5]. The Kinect system features a built-in motion capture program that processes time-series depth images and extracts joint locations to represent movement over time. Most studies that emphasized specific gait features such as step or stride length used the Kinect. This characteristic grants the Kinect, and depth cameras in general, a significant advantage in interpretability and reliability over alternative technologies.

3.1.3 Radio Frequency (RF) Devices. Five studies explored RF devices, including ultra-wideband, micro-Doppler, mmWave radars, and WiFi [24, 13, 2, 14, 12]. While the radars are overall slightly less accurate than utilizing cameras, they have the advantage of protecting privacy and allowing for ambient analysis of an individual going about their normal routine at home. For these studies, the micro-Doppler signatures were the immediate product of the sensor. While a subset of gait parameters, such as speed, stride length, and step length, can be extracted from them, most studies adopt an end-to-end pipeline that directly maps neurodegenerative diseases to micro-Doppler signatures using data-driven models.

3.2 Key Features

We analyze key gait features associated with neurodegenerative diseases with a focus on Parkinson's and dementia as they are the primary diseases examined in identified studies.

3.2.1 Parkinson's. Surveyed studies found that the key gait feature for identifying Parkinsonism is gait speed. Many studies established that subjects with some degree of Parkinsonism had lower gait speed than healthy controls. These studies found a minuscule p-value (<0.005) when comparing the gait speed of healthy subjects and those affected by Parkinsonism [22, 25]. Arm swing was found to be important for distinguishing Parkinsonism, but of relatively lower importance for determining the stage of the disease [25]. However, a study comparing Parkinsonism to spinocerebellar degeneration found that the latter affliction causes more severe gait abnormalities [11]. Cadence and symmetry were also found to have significance for classifying Parkinsonian gait [26].

3.2.2 Dementia. Lower cadence and step width were found to be clear associations with dementia [3, 22, 32, 18]. In addition, it was found that analyzing the frequency domain delivers better results than analyzing the time domain [24].

3.3 Analytical Methods

The wireless sensing-based gait analysis methods in the surveyed studies fall into two categories: descriptive statistics and data-driven analysis.

3.3.1 Descriptive Statistics. With joint locations provided by Kinect and camera systems through the built-in motion capture algorithm

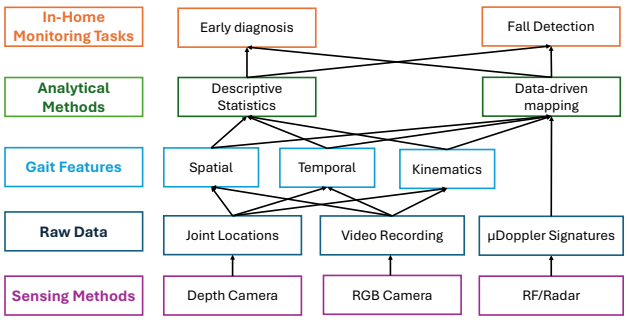


Figure 2: Workflow for wireless gait sensing tasks. The depth and RGB camera systems can generate gait features, allowing for an explainable analysis of the association between neurodegenerative diseases and related events, based on descriptive statistics. These gait features are typically categorized into four clinically relevant metrics: spatial, temporal, kinematics, and kinetics. However, kinetics are generally not accessible through wireless sensing technologies. On the other hand, RF/radar-based methods generally employ an end-to-end pipeline, where micro-Doppler signatures serve as input to data-driven models, for direct mapping to neurodegenerative diseases or associated events, such as falls.

or computer vision technologies such as OpenPose [4], spatial, temporal, and kinematic gait parameters can be derived. These clinically aligned gait parameters enable several studies to use descriptive statistics to establish explainable associations with neurodegenerative diseases and related events [25, 22, 27, 13].

3.3.2 Data-Driven. With advances in machine learning and deep learning, many studies apply data-driven approaches to map sensing features directly to neurodegenerative diseases and related events. This bypasses the need to examine their association with clinically aligned gait metrics, which may not be readily available in certain sensor modalities, such as radar.

For example, three studies [12, 31, 27] included in Table 2 and two [5, 14] in Table 3 explored LSTM models in the dementia assessment and gait analysis. Three studies utilized CNNs for gait analysis [33, 24, 5]. Four studies used a support vector machine (SVM) for data analysis [3, 33, 27, 5].

3.4 Remarks

We visualize the general workflow for wireless gait analysis in Figure 2. Overall, both the Kinect system and RF/radar sensing prove to be effective ways to accurately measure various gait features across a wide variety of testing environments. Step speed and step length appear to consistently be strong discriminators for the identification of both Parkinson's and Alzheimer's-related gait disorders. Studies using basic statistical models instead of end-to-end data-driven approaches yielded less precision but greater explainability. However, conclusively attributing predictive value to any specific gait feature remains challenging due to significant variability in parameters, sensors, and analysis methods across existing studies. Furthermore, while many purpose-built models achieve strong results in their intended use cases, it is unclear whether their performance can generalize to broader datasets.

4 Discussion

4.1 Current Status of Research

This scoping review offers a comprehensive overview of recent studies using wireless sensing for gait analysis in the assessment and management of neurodegenerative diseases. While the surveyed studies demonstrate the feasibility of wireless gait sensing in this context, they are exploratory in nature. Many practical challenges, however, remain yet to be addressed for real-world applications. For example, compared to controlled instrumented settings, variabilities in free-living environments pose generalizability challenges. Given the limited space, this discussion highlights three key aspects to address the challenges and opportunities, though further research is needed in many other areas.

4.2 Challenges and Opportunities

4.2.1 Datasets. While gait speed and step length are key features for various classification models in the surveyed studies, they are general indicators. Identifying and evaluating biomarkers specific to PD and ADRD should remain a priority. Additionally, it is crucial to adjust for factors such as age, height, physical condition, and environmental settings to ensure generalization across diverse demographic groups. However, the absence of a large, standardized dataset significantly impedes this field of research. As investigators are working primarily off new data, it is not easy to effectively compare results between studies. A key future direction is the development of standardized datasets for benchmarking methods with respect to modeling the aforementioned aspects in this context. In addition, such health datasets should be synthetic and abstracted in order to protect the subject privacy, while ensuring consistent application of diagnostic criteria for ground truth labeling. Developing infrastructure to support community-driven data collection and benchmark development is a critical area of future research to address the challenges outlined above.

4.2.2 Sensor Modalities. Compared to wearable alternatives, wireless solutions eliminate the need for frequent charging and continuous user compliance. However, wireless sensing relies on infrastructure and operates within a limited range, particularly for cameras and Kinect systems, which require a clear line of sight (LOS). Moreover, radar signals are sensitive to interference. A further weakness of radar sensors is the relatively high cost in human expertise to manage such a system as opposed to consumer-grade cameras. Additionally, wireless sensing approaches typically cannot measure kinetic gait parameters, which can be complemented by pressure or floor vibration sensing [8, 9]. Integrating multiple modalities is a promising approach to maximize complementarity across factors such as sensitivity, resolution, sensing range, and computational cost.

4.2.3 In-home Deployment. Adopting wireless sensors as an in-home system might require technical knowledge a patient may not possess. Furthermore, with in-home monitoring systems, real-time analysis would require either the local availability of computing resources or the existence of a secure cloud platform for processing

privacy-sensitive health data. These logistical issues, which limit the utility of this technology in practical scenarios, may be best addressed by the development of a scalable infrastructure with streamlined setup and maintenance requirements [20].

5 Conclusion

This study synthesized the results of the available studies on wireless sensing of gait for the assessment of neurodegenerative diseases, with a focus on Parkinsonism and ADRD. Specifically, we examined gait features and analytical methods that facilitate wireless sensing for neurodegenerative disease assessment, aiming to understand prevailing practices and the current state of research in this field. Based on these findings, we highlight key challenges and opportunities related to datasets, sensor modalities, and practical in-home deployment to guide future research.

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