Markerless Motion Capture to quantify functional performance in neurodegeneration: A systematic review

Julian Jeyasingh-Jacob, Mark Crook-Rumsey, Harshvi Shah, Theresita Joseph, Subati Abulikemu, Sarah Daniels, David J. Sharp, Shlomi Haar

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Abstract

Background: Markerless motion capture (MMC) uses video cameras and/or depth sensors for full body tracking and presents a promising approach for objectively and unobtrusively monitoring functional performance within community settings, to aid clinical decision-making in neurodegenerative diseases such as dementia.

Objective: The primary objective of our systematic review was to investigate the application of MMC using full-body tracking to quantify functional performance in people with dementia, mild cognitive impairment (MCI) and Parkinson's disease (PD)

Methods: We systematically searched for relevant articles which yielded a total of 1595 results. Inclusion criteria were MMC and full-body tracking. A total of 157 studies were included for full article screening out of which 26 eligible studies that met the selection criteria were included in the review.?

Results: Primarily, the selected studies focused on gait analysis, while other functional tasks, such as sit-to-stand and stepping in place, were also explored. However, activities of daily living were not evaluated in any of the studies. MMC models varied across the studies encompassing depth cameras vs standard video cameras or mobile phone cameras with postprocessing using deep-learning model. However, only a few studies conducted rigorous comparisons with established ground-truths.

Conclusions: Despite its potential as an effective tool for analysing movement and posture in individuals with dementia, MCI, and PD, further research is required to establish the clinical usefulness of MMC in quantifying mobility and functional performance in the real-world.

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Conclusion: Despite its potential as an effective tool for analysing movement and posture in individuals with dementia, MCI, and PD, further research is required to establish the clinical usefulness of MMC in quantifying mobility and functional performance in the real-world.

Introduction

Markerless motion capture (MMC) technology uses sensors and advanced software algorithms to track and analyse human movement, without the attaching of physical markers to individuals or use of external devices such as pressure sensors or wearables. There is growing use of MMC to provide highly accurate and quantifiable information on key functional parameters such as mobility[1],[2], balance[3], upper extremity tasks[4], and activities of daily living (ADL)[5].

While three-dimensional movement capture systems using markers are considered the gold standard for movement analysis, they have several limitations including their lack of portability,

need for trained staff, and requirement for reflective markers to be placed precisely on participants' bodies[6]. The use of MMC provides several advantages in comparison: being easier to operate, requiring less space, and cheaper than traditional marker-based systems[7]. Importantly, their ability to capture movement unobtrusively is a key benefit for user compliance[8], particularly when working with cognitively impaired individuals.

MMC is attractive for healthcare and research use, such as to detect and monitor functional performance in conditions where this can be affected, for example, neurodegenerative diseases. While traditional movement analyses are based on subjective clinical assessments, MMC can be used to generate objective and quantifiable digital biomarkers that can help detect declines in functional performance and ADLs by capturing movement unobtrusively. Variations in these digital biomarkers could indicate underlying impairment and enable earlier support. The fact that MMC can be deployed in home environments may avoid unnecessary hospital visits for patients, as well as detect subtle changes in functional ability that may be only apparent in everyday home-based settings than within a clinic.

There are several MMC devices which can provide cost-effective assessments of functional performance in research and clinical settings. Broadly, the two main types of MMC camera hardware are depth cameras and standard RGB (Red Green Blue) video cameras, used in single or multi-camera systems. Commonly used and widely accessible depth cameras are the Microsoft Kinect devices, which use standard RGB colour video as well as depth estimation through recording the distance between the camera and each pixel through the emission of structured light patterns[9]. Machine learning algorithms can be used to reconstruct 3D skeletal models in real time from the RGB-D (RGB + depth) image. Alternatively, deep learning can be used with standard video cameras or mobile phone cameras to record limb location and orientation. This method uses deep neural networks trained from large datasets to estimate body segment position and orientation (pose), and motion tracking, without explicit depth sensing. It requires specific body segment positions known as the six degrees of freedom; three rotational (flexion/extension, abduction/adduction and rotation about the longitudinal axis) and three translational (sagittal, frontal and transverse) [10]. Both forms of MMC have shown promising use thus far.

A scoping review of single camera MMC models used in healthcare highlighted significant potential for use in clinical applications, but also noted the need to improve their tracking accuracy[11]. A previous systematic review of MMC-based training devices used in neurological rehabilitation found that these devices improve motivation and enable better functional performance potentially due to the gaming element[12]. Another systematic review of MMC-based devices in rehabilitation found that balance training with the support of MMC resulted in better outcomes potentially due to more dynamic training conditions[13]. While these systematic reviews explored the use of MMC specifically in rehabilitation training, our review focus on technology-based evaluation of functional tasks. The recent increase in the number of studies involving MMC based movement analysis in neurodegenerative diseases offers a strong rationale for our current study. This includes the use of MMC for tracking gait decline[14], assessing falls risks[15], technology-based tools that could

replace clinical measures[16], detect disease traits[17], estimate disease severity[18], and detect cognitive impairment from gait features[19].

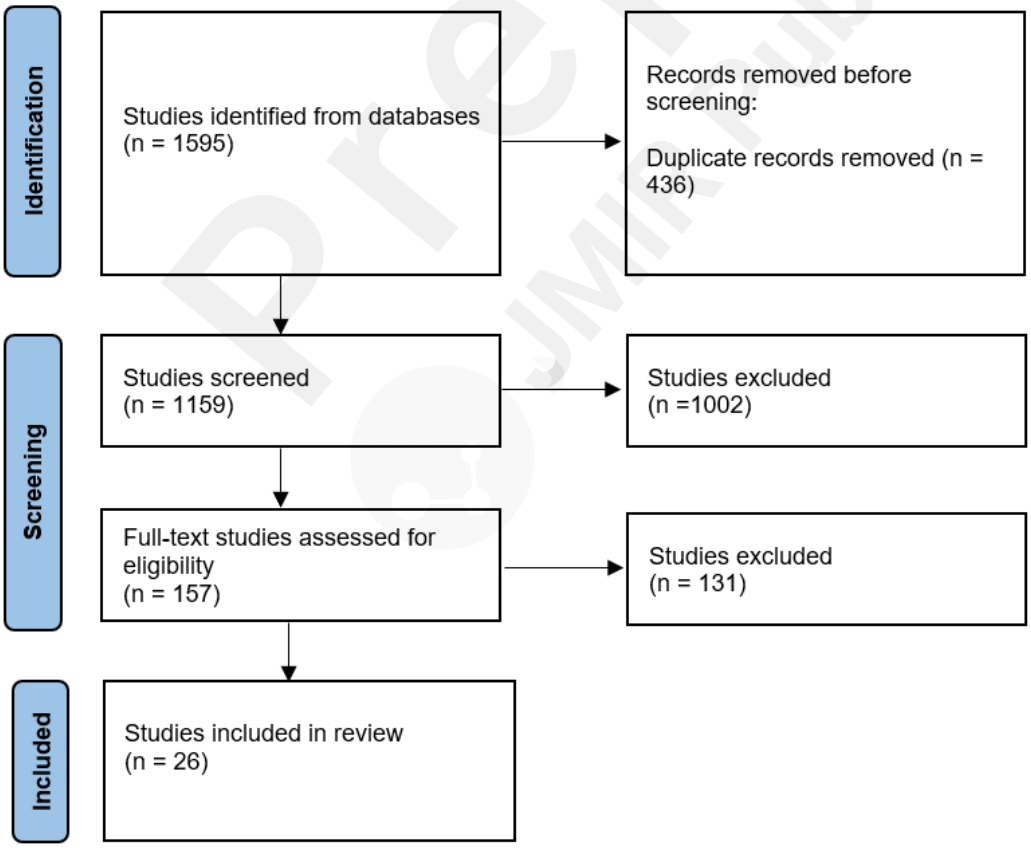
Neurodegenerative diseases such as dementia and Parkinson's disease (PD) lead to declining functional performance. Detecting problems in everyday functional tasks in these patient groups can help provide early, timely, and clinically appropriate interventions that may help maintain independence, decrease caregiver burden, and potentially slow the rate of functional decline [20,21]. MMC can provide digitally measured functional performance data that could be used to enhance clinical decision-making and remote monitoring, identify risks such as falls, and better capture the impact of rehabilitative, pharmacological and surgical interventions. Although MMC technology could offer potential for detecting functional changes in neurodegenerative diseases, a model that is comparable to ground truths is essential for deployment in real-world applications. The aim of this study was to complete a systematic review of published literature on the use of MMC with full-body tracking for quantifying functional performance in people with dementia, MCI, and PD.

Results

Study selection

The literature search yielded 1595 results, after removing duplicates, 1159 studies were left for title or abstract screening. 131 studies remained for full article screening, of which only 26 studies met the inclusion criteria and were included in the review. A PRISMA flowchart [22] outlining the selection process can be found in [Figure 1].

Fig. 1 PRISMA 2020 flow diagram for new systematic reviews



Quality assessment

The 26 selected studies were assessed for quality using the Specialist Unit for Review Evidence (SURE) questions to assist with the critical appraisal of cross-sectional studies tool[23]. No studies were excluded from the review based on the quality assessment.

[Table 1: Quality assessment summary]

	Is the study design clearly stated?	Are the setting, location and relevant dates provided?	Were participants fairly selected?	Are participant characteristics provided?	Are the measures of exposures & outcomes appropriate?	Is there a description of how the study size was arrived at?	Is there information on how missing data was handled and sources of bias controlled for?	Is information provided on participant eligibility?	Are results well describ
Cimolin et al., 2022	✓	✓	✓	✓	✓	X	X	X	Not report
Kaur et al., 2022	✓	✓	Not reported	✓	✓	X	X	X	✓
Khan et al., 2021	✓	✓	Not reported	✓	✓	X	X	X	X
Khan et al., 2013	X	✓	Not reported	X	✓	X	X	X	X
Kondragunta et al., 2020	X	✓	Not reported	X	✓	Not reported	X	X	X
Lai et al., 2022	✓	✓	✓	✓	✓	X	X	X	✓
Li et al., 2018	X	✓	Not reported	X	✓	X	X	X	✓
Mehdizadeh et al., 2021a	✓	✓	✓	✓	✓	X	X	✓	✓
Mehdizadeh et al., 2021b	✓	✓	✓	✓	✓	✓	X	✓	✓
Morinan et al., 2022	✓	✓	X	X	✓	X	X	X	X
Munoz-Ospina et al., 2022	✓	✓	Not reported	✓	✓	X	X	X	✓
Ng et al., 2020	✓	✓	✓	✓	✓	X	X	X	✓
Ospina et al., 2018	✓	✓	✓	✓	✓	X	X	X	✓
Otte et al., 2020	✓	✓	✓	✓	✓	✓	✓	X	✓
Pedro et al., 2020	X	Not reported	Not reported	✓	✓	X	X	X	X

Prochazka et al., 2015	X	Not reported	Not reported	X	✓	X	X	X	✓
Rupprechter et al., 2021	✓	X	Not reported	X	✓	X	X	X	✓
Sabo et al., 2022a	✓	✓	✓	✓	✓	X	X	X	✓
Sabo et al., 2022b	✓	✓	Not reported	✓	✓	X	X	X	✓
Sabo et al., 2021	✓	✓	Not reported	X	✓	X	X	X	X
Sabo et al., 2020	✓	X	Not reported	✓	✓	X	X	X	✓
Seifallahi et al., 2022	✓	Not reported	Not reported	X	✓	X	X	X	✓
Shin et al., 2021	✓	✓	✓	✓	✓	X	X	X	✓
Soltaninejad et al., 2018	X	✓	Not reported	X	✓	X	X	X	✓
Tan et al., 2019	✓	Not reported	✓	✓	✓	✓	X	X	✓
Tupa et al., 2015	✓	✓	Not reported	X	✓	X	X	X	✓

Patient groups

The 26 studies included 18 with PD patients, 6 with dementia patients, and 2 with MCI patients. Most of the studies used a Kinect sensors for MMC. All studies that included participants with dementia (n=6) used the Kinect sensor and were conducted in inpatient settings. The Kinect was used to quantify gait decline over a 10-week period[14], propose a prognostic model for falls risk[15] , and demonstrate association with clinical gait measures and future falls[16]. In dementia inpatients with drug-induced parkinsonism, the Kinect was used to capture parkinsonian traits [17], quantify parkinsonian gait [24] and along with pose estimation of recordings from a video camera estimate parkinsonian severity[18]. It was also used in the MCI studies reviewed (n=2), as a tool to detect mild cognitive impairment (MCI) from gait features [19,25].

Of the 18 studies that included PD patients, 10 reported the use of the Kinect sensor for analysing gait, including its feasibility to extract relevant features [26,27] ability to detect PD [28–31], and ability to measure clinical disease severity [32–34]. Alternative MMC models using image processing for pose estimation from videos recorded with RGB cameras have also been used with PD patients demonstrating the feasibility of these models in quantifying gait impairment and disease severity [18,35–41].

Functional performance components

Most studies (n=24) evaluated aspects of gait, although there were significant variations in the features extracted and methods used for analysis, with some of them lacking statistical significance. Other functional performance components evaluated were sit-to-stand (n=5) and stepping in place (n=1). [Table 2] shows functional performance components by study.

Feature categories

[Table 2] shows extraction feature categories by study. Spatiotemporal features of gait that were reported as having statistical significance included spatial parameters such as step length (n= 8), step width (n= 5) and stride length (n= 4), and temporal parameters such as cadence (n=5), gait velocity (n=4), step time (n= 4), stance duration (n= 1), double support duration (n= 1), stride time (n= 1), turning time (n= 1), turning speed (n= 1), swing time (n= 1), step velocity (n= 1), and stride velocity (n=1). Other extracted feature categories included symmetry (n=9), stability (n=8), range of motion (ROM) (n=2) and rhythmicity (n=1).

[Table 2: Patient groups, functional performance components and feature extraction categories]

Study	Patient Group	Functional Performance Component	Feature Category
Cimolin et al., 2022	PD	Gait	Spatio-temporal, Stability
Kaur et al., 2022	PD	Gait	Spatio-temporal, Symmetry
Khan et al., 2021	PD	Gait	Spatio-temporal

Khan et al., 2013	PD	Gait	Gait posture. Spatio-temporal
Kondragunta et al., 2020	MCI	Gait	Spatio-temporal
Lai et al., 2022	PD	Gait	Spatiotemporal, ROM
Li et al., 2018	PD	Sit to stand Gait	Spatio-temporal
Mehdizadeh et al., 2021a	Dementia	Gait	Spatio-temporal, ROM, Stability
Mehdizadeh et al., 2021b	Dementia	Gait	Spatio-temporal, Stability, Symmetry
Morinan et al., 2022	PD	Sit to stand	Spatio-temporal
Munoz-Ospina et al., 2022	PD	Gait	Spatio-temporal, Symmetry
Ng et al., 2020	Dementia	Gait	Stability
Ospina et al., 2018	PD	Gait	Spatio-temporal, Symmetry
Otte et al., 2020	PD	Stepping in place	Spatio-temporal, Symmetry, Rhythmicity
Pedro et al., 2020	PD	Gait	Spatio-temporal
Prochazka et al., 2015	PD	Gait	Spatio-temporal
Rupprechter et al., 2021	PD	Gait	Spatio-temporal
Sabo et al., 2022a	PD	Gait	Spatio-temporal
Sabo et al., 2022b	Dementia	Gait	Spatio-temporal, Stability, Symmetry
Sabo et al., 2021	Dementia	Gait	Spatio-temporal, Stability, Symmetry

Sabo et al., 2020	Dementia	Gait	Spatio-temporal, Stability, Symmetry
Seifallahi et al., 2022	MCI	Gait	Spatio-temporal
Shin et al., 2021	PD	Gait Sit to stand	Spatio-temporal
Soltaninejad et al., 2018	PD	Gait Sit to stand	Spatio-temporal
Tan et al., 2019	PD	Gait Sit to stand	Spatio-temporal, Stability
Tupa et al., 2015	PD	Gait	Spatio-temporal

ROM = Range of motion; PD = Parkinson's Disease; MCI = Mild Cognitive Impairment

MMC devices and feature extraction methods

[Table 3] shows that most studies used Kinect depth cameras (4 used V1, 12 used V2, one used Kinect eMotion and the latest version the Azure Kinect was used in one study), while the remainder used regular video or mobile phone cameras. Common camera positioning included frontal views (n=4), ceiling-mounted (n=4) and multiple cameras from different angles (n=3). However, camera position was not reported in seven of the study articles. The majority of studies have developed their own custom programs (n=10) or have used Opensource libraries (n=8) to identify bodies in frame and extract movements. The use of propriety software was less common (n=5).

[Table 3: MMC Devices and feature extraction methods used]

Study	Device (Camera/ Sensor)	No. of Devices	Frames per second (fps / Hz)	Position of Cameras	Extraction Methods
Cimolin et al., 2022	Kinect V2	1	30	Tripod in front	Custom algorithm
Kaur et al., 2022	Video camera	2	30	Front and right side	OpenPose
Khan et al., 2021	Video camera	1	25	Front	Custom algorithm
Khan et al., 2013	Video camera	1	5	Not reported	Custom algorithm
Kondragunta et al., 2020	Kinect V2	1	20	Not reported	OpenPose
Lai et al., 2022	Kinect V2	Not reported	30	Not reported	GaitBEST
Li et al., 2018	Video camera	1	25	Not reported	Iterative Error Feedback &

					OpenPose
Mehdizadeh et al., 2021a	Kinect V2	1	Not reported	Ceiling in hallway	Custom algorithm
Mehdizadeh et al., 2021b	Kinect V2	1	Not reported	Ceiling in hallway	Custom algorithm
Morinan et al., 2022	Mobile phone camera. KELVIN-PD mobile application (Machine Medicine)	Not reported	Not reported	Not reported	OpenPose
Munoz-Ospina et al., 2022	Kinect eMotion	1	Not reported	Not reported	Custom algorithm
Ng et al., 2020	Kinect V2	1	30	Ceiling at the end of a hallway	OpenPose
Ospina et al., 2018	Kinect V1	1	Not reported	Participants walking towards the camera	Custom algorithm
Otte et al., 2020	Kinect V1	1	30	1.4m height in front	Custom algorithm
Pedro et al., 2020	Azure Kinect	3	30	Each end of walkway and halfway between	Azure Kinect SDK to extract joint positions to estimate 32 body joint poses from depth colour recordings.
Prochazka et al., 2015	Kinect V1	1	30	60 cm above floor	Custom algorithm
Rupprechter et al., 2021	Mobile phone camera. KELVIN-PD mobile application (Machine Medicine)	1	Not reported	Patients walking directly towards and/or away from the camera in hallways or office settings	OpenPose
Sabo et al., 2022a	Logitech C920	1	30	Tripod mounted, at one end of walkway	AlphaPose, Detectron, OpenPose, ROMP
Sabo et al., 2022b	Kinect V2	1	30	Kinect- hallway ceiling Stationary	OpenPose, Detectron, AlphaPose

	Mobile phone cameras			mobile phone camera- participants walked towards and away from	
Sabo et al., 2021	Kinect V2	1	30	Ceiling in hallway	AlphaPose, engineered 2D gait features from joint trajectories
Sabo et al., 2020	Kinect V2	1	30	Ceiling in hallway	OpenPose
Seifallahi et al., 2022	Kinect V2	1	Not reported	On a tripod at a suitable distance from an oval path	Custom algorithm
Shin et al., 2021	Video camera	1	30	Frontal view from a tripod mounted camera 1.5 metres from the horizontal line of the turning point	OpenPose, OpenCV
Soltaninejad et al., 2018	Kinect V2	Not reported	30	Not reported	Graph model of body skeleton
Tan et al., 2019	Kinect V2	C1	Not reported	End of walkway	Custom algorithm
Tupa et al., 2015	Kinect V1	1	30	60 cm above floor	Custom algorithm

Key findings

[Table 4] summarizes the key findings of the 26 studies that utilised MMC to study movement features in people with dementia, MCI, and PD. Stride length, cadence, gait stability, step length, arm swing, and number of steps were the primary features investigated in these studies. Notably, several studies[32,34,36,42] found that stride length and cadence are commonly affected in those with Parkinson's disease. Other studies [15,24,33] highlighted the potential of MMC for predicting fall risk and discriminating between individuals with PD and controls.
Most studies used some form of clinical validation for assessment of disease, and patients were referred to or were assessed within a clinical research facility by a clinician. The most common clinical measures used were the Unified Parkinson's Disease Rating Scale (UPDRS) for assessing Parkinsonism symptoms in those with PD and dementia and the Performance Oriented Mobility Assessment (POMA)-gait and POMA–balance assessments for evaluating mobility

characteristics. Many of the studies used the MMC features to classify patients from control participants and to classify symptoms severity (e.g., UPDRS scores in PD) using various techniques, including Support Vector Machines, Random Forest Models, Multivariate Ordinal Logistic Regression, and Adaptive Neuro-fuzzy Inference System classifiers. Several studies reported excellent classification accuracy, with some achieving 100% accuracy [31,36,37]. For instance, Seifallahi et al.[25] achieved an accuracy of over 90% for differentiating between people with mild cognitive impairment and controls using an Adaptive Neuro-fuzzy Inference System classifier. Khan et al.[36] reported a 70.83% accuracy in predicting UPDRS-gait scores using a SVM model, with an area under the ROC curve of 80.88%.

Conversely, most studies included within this review (n=20) did not employ a ground-truth to evaluate their MMC system or algorithms, making it difficult to conclude whether their derived features for monitoring functional performance characteristics were comparable to an accepted measure of movement analysis. Some notable exceptions such as Cimolin et al.[28] compared their Kinect setup to a Vicon system, which is an accepted and clinically validated method for assessing gait. Other studies used established and clinically validated spatiotemporal measures including the GAITRite system[26,41] and the Zeno Walkway system[42], although Pedro et al.[26] only had two participants. Li et al.[38] had experts manually annotate videos, which, while subjective, proved effective for creating labels to train machine learning algorithms for task segmentation. They also used automated labelling to generate sub-task segmentation, which could be helpful for automating larger scale studies and clinical assessments.

MMC models showed moderate to strong positive corelations with Vicon[28] , Zeno[42] and GAITRite [41]. However, some of the studies also identified limitations of MMC. For example, Pedro et al.[26] found that Kinect cameras may overestimate step length variation in people with PD due to inherent smoothing, while Sabo et al.[42] found that automated heel strike algorithms may struggle to identify short steps. Some studies[19,38] reported challenges with data processing and interpretation, highlighting the need for more standardised methods in this field.

Despite these limitations, the findings suggest that MMC is a promising tool for studying characteristics of functional performance in people with dementia, MCI, and PD. It is worth noting that specialised depth cameras may not be necessary for extracting suitable joint positions in camera space[42]. However, further research in this field is warranted to fully understand the potential of MMC.

[Table 4: Key findings]

Study	**Primary feature(s)**	**Main result(s)**
Cimolin et al., 2022	Gait cadence, mediolateral sway and step width	Strong positive correlation between Kinect and Vicon systems for gait cadence and mediolateral sway (ICC 0.94-0.97) and weak correlation for step width (ICC 0.44) in PLWPD.
Kaur et al., 2022	Stride (91 derived features based on variation, asymmetry speed)	Logistic regression, random forest, DL based classifiers 75% (walking & talking) and 78.1% (walking)

		Multi-scale residual neural network: 100% accuracy for classifying people with controls, Multiple sclerosis & PLWPD during walking and walking-while-talking, 78% for new subjects walking. 1D Convolutional neural network: 75% walking-while-talking, 79.3% when generalising to new subjects in different tasks
Khan et al., 2021	Slow walking Short-shuffling steps Gait festination	SVM classification predicts UPDRS- gait scores with 70.83% accuracy and area under ROC curve 80.88%
Khan et al., 2013	Stride-cycles, posture lean	SVM classification of 100% for differentiating between PD and controls
Kondragunta et al., 2020	Gait cycle (dynamic time warping)	SVM for classifying between controls, persons with possible MCI and persons with MCI: 74.6 – 87.3%
Lai et al., 2022	Stride length, straight walking speed, turning speed	Mediation analysis demonstrates decreased stride length, walking speed, turning speed are associated with increased fall prediction model score (r = -.58, r = -.52, r = -.46, respectively; ps < .0001) UPDRS negatively correlated with features (r = -.65, r = -.56, r = -.37, respectively; ps < .0001) but positively with fall prediction model score (r = .53, p < .0001) UPDRS serves as mediators for features and higher fall prediction model score.
Li et al., 2018	Sub-task segmentation based on selected body points: neck, R/L shoulder, R/L hip, R/L knee, R/L ankle	Accuracies for sub-task segmentation of TUG: OpenPose + LSTM = 93.10%, OpenPose + SVM = 92.8% Correlations between OpenPose + LSTM & experts on *timed reduction rates:* Turn (0.93), walk-back (0.98), sit-back (0.98)
Mehdizadeh et al., 2021a	Gait stability, step time, step length, step time variability, step length variability	Mixed effects models over 10 weeks show: decrease in primary features and an increase in variability over time for PLWD. Gait stability decreased more in men. Mediolateral range of motion decreased in those

		with mild neuropsychiatric symptoms but increased in those with more severe symptoms.
Mehdizadeh et al., 2021b	Gait stability	Cox proportional hazard regressions show gait stability predicts time to fall in PWLD (ROC .80 at 7 days, .67 30 days)
Morinan et al., 2022	D_{body} = distance between nose and two ankles. Std of D_{body}, Proportional increase in $D_{body,}$ Percentage jerk of $D_{body.}$ D_{hand} = distance between two wrists. U = hands used (Boolean)	Ordinal random forest classifiers: U = 99.6% accuracy for hands used to push up from chair. UPDRS ratings estimated by models agree 79.2% with clinicians' ratings for PLWPD
Munoz-Ospina et al., 2022	Left & right arm and ankle swing (magnitude, speed), stance time, gait speed, total time, number of steps	Random forest model was most accurate for discriminating between PD and controls (85% using all gait features)
Ng et al., 2020	Gait: Cadence, symmetry, CV of step time, step width (average & CV), eMOS	Univariate linear regression – Cadence associated with POMA-gait scores (p = 0.00047) Poisson regression: cadence, eMOS, average step width associated with number of future falls (ps < 0.05)
Ospina et al., 2018	Arm swing (magnitude, time, arm swing asymmetry	Age influenced arm movement. PLWPD showed significant reductions in arm swing magnitude and speed (ps < 0.01). Arm swing asymmetry differentiated PD from controls (ROC: 78%).
Otte et al., 2020	Cadence, knee amplitude, asymmetry, average step time, longest step time, arrhythmicity, average stance time, longest stance time	Knee amplitude, longest stance time correlated with UPDRS (-.51, p = .003, 0.52, p = 0.002, respectively). Postural instability (pull test) correlated with longest stance time (0.47, p = 0.008). Knee amplitude, asymmetry, average step time differed between on and off medication states (ps < 0.01)
Pedro et al., 2020	Step length	In comparison with the GAITRite system, the Kinect camera overestimated average variation in step length for the 2 PWLPD subjects potentially due to inherent smoothing.
Prochazka et al., 2015	Average step length	91.7% classification accuracy for determining between controls and those with PD. Decrease in step length (regression coef = -0.0082 m/year)
Rupprechter et al., 2021	Steps, arm swing, postural control, smoothness	Step frequency highly correlated with labelled steps (p < 0.001) Ordinal random forest: 50% prediction

Sabo et al., 2022a	Number of steps, cadence, velocity, step length, CV of stride width, step and swing time.	Moderate/strong positive correlations between steps, cadence, step width from 2D pose-estimation and Zeno in PLWPD. Automated heel strike algorithm struggled to identify short steps.
Sabo et al., 2022b	Cadence, steps, average step width, average margin of stability, CV of step width and time, symmetry, stability	ST-GCN operating on 3D joint trajectories outperform 2D models. Best model prediction of UPDRS-gait and SAS-gait scores = 53% and 40%, respectively.
Sabo et al., 2021	Cadence, steps, average step width, average margin of stability, CV of step width and time, symmetry	ST-GCN using 2D joint trajectories and gait features outperform ST-GCN using only gait features. Regression models for predicting UPDRS-gait over 94% if off by 1 is allowed.
Sabo et al., 2020	2D: Steps, cadence, symmetry, CV of step time. 3D: walking speed, step length/width, step width, step length symmetry angle, RMS of ML velocity, Margin of stability, CV step width	Multivariate ordinal logistic regression models achieved 61.4 & 62.1% for 2D and 3D features for predicting UPDRS-gait in PLWD
Seifallahi et al., 2022	Steps, stride	Adaptive Neuro-fuzzy Inference System classifier accuracy > 90% for differentiating between MCI and controls
Shin et al., 2021	Step length, gait velocity, number of steps, turning time	Features correlated with Freezing of Gait questionnaire, Unified PD rating scale part III total score, HY and postural instability in PLWPD. Features measured improvements following medication.
Soltaninejad et al., 2018	Stride, tremor	Random forest classifier accuracy for differentiating controls and PLWD: 93.33% stride, 81% tremor.
Tan et al., 2019	Step length, step time, vertical pelvic displacement, gait speed	Multivariable regression: step length during TUG and vertical pelvic displacement during the gait speed were associated with postural gait instability and gait disorder ($p < 0.05$) in PLWPD
Tupa et al., 2015	Step length, average speed	Combining gait features improves classification accuracy relative to single features.

		Two layer neural-network achieved an accuracy of 97.2% in classifying PLWPD from controls.

SVM = Support vector machine; UPDRS = Unified Parkinson's Disease Rating Scale' PLWD = people living with dementia, PLWPD = people living with Parkinson's Disease, CV = Coefficient of variation, RMS = Root Mean Squared, ML = Medio-lateral, MCI = Mild Cognitive Impairment, TUG = timed-up-and-go, LSTM = Long short-term memory (machine learning model), eMOS = estimated margin of stability, ST-GCN = Spatio-temporal graph convolutional networks

Discussion

In this study, we completed a systematic review of the use of MMC with full-body tracking for quantifying function in people with dementia, MCI and PD. The lack of standardization in the models used prevented us from comparing and synthesizing study results via a meta-analysis.

The review findings suggest that there is more evidence of the use of MMC with full-body tracking in patients with PD (n=18) compared to those with dementia (n=6) and MCI (n=2). This demonstrates a bias towards movement disorders, where the motor symptoms are more prominent, and highlight a significant knowledge gap in the feasibility and effectiveness of using MMC models in quantifying functional performance in people with dementia and MCI. Moreover, the studies that included patients with dementia [14–18,24] were all conducted in inpatient dementia units, indicating a lack of research involving this patient group in real-world settings. This underscores the need for further investigation in this area.

While MMC models based on gait features extracted mainly from straight-line walking may provide useful preliminary data for model development, they have less scope in quantifying functional performance in a real-world context, particularly in people with cognitive impairment. In contrast, the evaluation of ADL tasks could potentially provide more comprehensive insights into real-world functional performance from routine daily activities. Previous research suggests that dual task tests of mobility are more effective in detecting cognitive decline as well as predicting cognitive impairment and falls[43–45] potentially due to the increased cognitive demand on the individual. However, just one study included in this review[19] utilised dual tasks for classification of MCI from control and it was not reported how the completion of dual tasks impacted the results. Feature extraction of ADL tasks that require planning and organisation could potentially facilitate the measurement of dual task performance. Therefore, analysis of ADL tasks could help provide a more accurate assessment of neurodegenerative impairment.

The findings of this review suggest a lack of consensus on the most effective features used. Some spatiotemporal features of mobility such as step length are commonly used, but other features vary widely between studies, making it difficult to determine which are most effective. Additionally, some unique features such as vertical pelvic displacement[27] and $D_{body,}$ the distance between nose and two ankles[39], have been identified in individual studies, but their effectiveness is unknown without further evaluation. Moreover, it is important to note that the effectiveness of several of these feature extraction models has not been tested in real-world settings which therefore requires further evaluation.

Several studies included in the review (n=10) reported machine learning classifier outcomes for identifying people living with dementia, MCI or PD from control[19,25,29–31,33,35–37,46] whereas several others (n=8) reported models that computed clinical assessment scores[17,18,24,34,38–41]. Although these are useful outcomes, it is important to note that

models that help detect gait impairment and predict falls (n=5)[14–16,27,32] could potentially be more useful in practical applications for assessing functional performance. It must also be noted that these models were all based on the Kinect cameras demonstrating the potential of RGB-D cameras for detecting and predicting functional impairment.

Accurate feature extraction and classification is crucial for improving the quality of MMC-based functional assessment[47]. The accuracy rates of MMC models reported in the reviewed studies ranged from 40% for a model predicting a clinical assessment score[18] to 100% for machine learning classification of PD from control[37]. Those numbers cannot be compared directly due to the different number of classes and the resulting chance level, as well as the task difficulty between classifying patients from control participant to rating symptoms. However, it is important to ensure that any clinical applications of these models are consistent and accurate because inaccurate predictions could potentially have consequences for patient care. Further validation and refinement of the models may therefore be necessary before they can be safely used in practical applications.

It is important to note that the accuracy of a model does not only depend on its ability to correctly identify a condition but also on its capacity to detect features of functional performance consistently in various real-world settings. The effectiveness of several feature extraction models reviewed in this study has not been tested in such settings, and therefore the accuracy in practical applications remains unclear. Moreover, many of the studies reviewed seem to have primarily focused on the technical aspects of the MMC models, such as feature extraction and analysis, with less focus on their clinical utility. This suggests that further research is needed to determine the usability of these models in clinical and real-world settings. Additionally, the cross-sectional nature of most of the included studies may limit their ability to evaluate and track functional performance over time. Longitudinal studies would be necessary to assess the performance of these models for tracking functional changes caused by factors such as disease progression, infections, and treatment effects or recovery. Despite these limitations, the effectiveness of MMC models using the Kinect[28] and 2D Pose Estimation[42] in comparison to ground truths within experimental settings suggests they may be suitable for testing in real-world applications such as remote monitoring.

It is important to consider the overall quality of studies included in this review, as shown in [Table 1] which summarises key questions to consider when assessing quality. Most studies had a clear study design and focused research questions with appropriate measures of exposures and outcomes. However, none of the studies reported if potential sources of bias from confounders such as musculoskeletal comorbidities, were controlled which could have implications for clinical applications. Studies that have attempted to create MMC models for fall prediction have primarily focused on retrospective analyses for example, number of falls in the past few months. While it is useful to examine historical patterns, future studies should aim to develop prospective studies. Testing the algorithms for MMC models in a prospective study would offer the capability to analyse more detailed information on fall events and contextual associated factors therefore making them more generalisable and valid for predicting falls.

The main findings of this review highlight the potential of MMC in assessing components of functional performance including gait and sit to stand characteristics in individuals with dementia, MCI and PD. Notably, high classification accuracies in several studies demonstrate the potential for clinical applications, such as identifying, monitoring, and predicting outcomes in

these populations. However, it is crucial to address the limitations and challenges, including overestimation of step length variation and difficulty in identifying short steps, as well as the need for standardised methodologies and further research.

Limitations

We were unable to conduct a meta-analysis of the reviewed studies due to the heterogeneity of the MMC models evaluated, the features extracted, and the analysis methods used. Additionally, the inclusion criterion of studies evaluating full-body tracking MMC models only meant that some studies analysing the movement of specific body parts were excluded from this review. Another limitation of our review is that only a small number of studies met the inclusion criteria limiting the generalisability of the study results.

Conclusion

Our findings illustrate that the use of MMC technology with full-body tracking has the potential to quantify functional performance in people living with dementia, MCI and PD. However, the lack of consistency in evaluating these models presents a challenge. Standardisation of the extracted features and analysis methods may help overcome the heterogeneity of the evaluation process and propose a framework for assessing future models. Our findings further suggest that MMC models based on both RGB-D and standard video cameras are viable options for analysing movement, yielding similar outcomes. Nonetheless, the RGB-D has been favoured in models intended to detect gait impairment and predict instances of falling.

It is worth noting that the majority of the reviewed studies evaluated aspects of gait, with no evidence of activities of daily living (ADL) tasks being analysed. Future studies should incorporate ADL tasks, as this would be more representative of real-world scenarios, particularly for individuals with cognitive impairment. Moreover, longitudinal studies are required to develop models that could track functional impairment over time and potentially predict decline.

Although accuracy is an important factor to consider when evaluating MMC models for clinical applications, other factors such as comparability to ground truths, and capability for analysing routine tasks and reproducibility in the natural environment are also important. Therefore, a more holistic approach to model development and evaluation with a clear focus on real-world clinical utility may be necessary to ensure that the models are suitable for use in practical applications.

Methods

We used the web-based Covidence software platform (Veritas Health Innovation, Melbourne, Australia) and the titles and abstracts were screened by two independent reviewers. The full text of the relevant studies was reviewed, and the quality of the studies assessed by two independent reviewers. Data extraction was also performed by two independent reviewers and any conflicts resolved through discussion.

Search strategy

The search strategy was designed to include all types of studies that used MMC with full-body tracking in individuals with dementia, MCI, or PD. To identify relevant studies, we used a combination of both the Medical Subject Headings (MeSH) thesaurus and free-text terms related to the three conditions and the MMC technology. Our search included publications from all years and the CINAHL, EMBASE, MEDLINE, and Scopus databases using the terms "Motion Capture," "Motion Analysis," "Movement Analysis" and “Pose Estimation” in combination with

"Dementia," "Mild cognitive impairment," and "Parkinson's disease" The details of the search activity can be found in the Supplementary Materials.

Inclusion and exclusion criteria

Our inclusion criteria for the systematic review were: (1) markerless optical motion capture, (2) full-body tracking, (3) involving participants with Dementia, MCI or PD, (4) original research, and (5) English language studies. Studies with the following characteristics were excluded: (1) motion capture with markers, inertial measurement units, body worn sensors or pressure sensors, (2) movement analysis of specific parts of the body or symptoms such as tremor and rigidity, (3) evaluating interventions such as exercises, deep brain stimulation, medication, rehabilitation protocol, dance and gaming, and (4) pose estimation of videos found on the internet.

Data extraction

The general information extracted from the studies included: centre and country where the study took place, study characteristics, funding sources, age, sex and number of participants, number and duration of visits, study aims, inclusion and exclusion criteria, and the main disease condition evaluated. Methodological information extracted included technical details of the MMC system used, functional performance area evaluated for example gait or sit to stand, software used for feature extraction, and the method of analysis. Results information extracted included: statistically significant movement features, whether they were measured under single or dual task (motor/cognitive) conditions, whether compared to ground truths or a relevant clinical measure, and key outcomes including the level of accuracy obtained.

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Author contributions

JJJ and SH wrote the review protocol, JJJ, MCR, HS, and TJ conducted the literature searches and performed data extraction. JJJ, MCR and SH wrote the paper. All authors read and critically commented on drafts of the study, including the latest version.

Conflicts of interests

None declared.

Abbreviations

MMC: markerless motion capture
MCI: mild cognitive impairment
PD: Parkinson's disease
ADL: activities of daily living
RGB: Red Green Blue
RGB-D: Red Green Blue-Depth
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SURE: Specialist Unit for Review Evidence
ROM: range of motion
UPDRS: Unified Parkinson's Disease Rating Scale

POMA: Performance Oriented Mobility Assessment
ROC: receiver operating characteristic
SVM: support vector machine
PLWD: people living with dementia
PLWPD: people living with Parkinson's Disease
CV: coefficient of variation
RMS: root mean squared
ML: medio-lateral
TUG: timed-up-and-go
LSTM: long short-term memory,
eMOS: estimated margin of stability
ST-GCN: spatio-temporal graph convolutional networks
MesH: Medical Subject Headings
CINAHL: Cumulative Index to Nursing and Allied Health Literature
EMBASE: Excerpta Medica database

Data availability

No new or unpublished data is included within the study and all data is freely available.

Code availability

All code relating to summary figure development is available on request to the corresponding authors.

References

1. Mentiplay BF, Perraton LG, Bower KJ, Pua Y-H, McGaw R, Heywood S, Clark RA. Gait assessment using the Microsoft Xbox One Kinect: Concurrent validity and inter-day reliability of spatiotemporal and kinematic variables. J Biomech 2015;48(10):2166–2170. doi: https://doi.org/10.1016/j.jbiomech.2015.05.021
2. Vernon S, Paterson K, Bower K, McGinley J, Miller K, Pua Y-H, Clark RA. Quantifying Individual Components of the Timed Up and Go Using the Kinect in People Living With Stroke. Neurorehabil Neural Repair 2015;29(1):48–53. doi: 10.1177/1545968314529475
3. Clark RA, Pua YH, Oliveira CC, Bower KJ, Thilarajah S, McGaw R, Hasanki K, Mentiplay BF. Reliability and concurrent validity of the Microsoft Xbox One Kinect for assessment of standing balance and postural control. Gait Posture Elsevier; 2015 Jul 1;42(2):210–213. PMID:26009500
4. Ma Y, Liu D, Cai L. Deep Learning-Based Upper Limb Functional Assessment Using a Single Kinect v2 Sensor. Sensors 2020;20(7). doi: 10.3390/s20071903
5. Rammer JR, Krzak JJ, Riedel SA, Harris GF. Evaluation of upper extremity movement characteristics during standardized pediatric functional assessment with a Kinect®-based markerless motion analysis system. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2014. p. 2525–2528. doi: 10.1109/EMBC.2014.6944136
6. Klöpfer-Krämer I, Brand A, Wackerle H, Müßig J, Kröger I, Augat P. Gait analysis – Available platforms for outcome assessment. Injury Elsevier; 2020 May 1;51:S90–S96. PMID:31767371
7. Bonnechère B, Jansen B, Salvia P, Bouzahouene H, Omelina L, Moiseev F, Sholukha V, Cornelis J, Rooze M, Van Sint Jan S. Validity and reliability of the Kinect within functional assessment activities: Comparison with standard stereophotogrammetry. Gait Posture 2014;39(1):593–598. doi: https://doi.org/10.1016/j.gaitpost.2013.09.018
8. van Dellen F, Hesse N, Labruyère R. Markerless motion tracking to quantify behavioral changes

during robot-assisted gait training: A validation study. Front Robot AI 2023 Mar 6;10. doi: 10.3389/frobt.2023.1155542
9. Wade L, Needham L, McGuigan P, Bilzon J. Applications and limitations of current markerless motion capture methods for clinical gait biomechanics. PeerJ 2022 Feb 25;10:e12995. doi: 10.7717/peerj.12995
10. Nakano N, Sakura T, Ueda K, Omura L, Kimura A, Iino Y, Fukashiro S, Yoshioka S. Evaluation of 3D Markerless Motion Capture Accuracy Using OpenPose With Multiple Video Cameras. Front Sports Act Living 2020 May 27;2. doi: 10.3389/fspor.2020.00050
11. Scott B, Seyres M, Philp F, Chadwick EK, Blana D. Healthcare applications of single camera markerless motion capture: a scoping review. PeerJ 2022 May 26;10:e13517. doi: 10.7717/peerj.13517
12. Knippenberg E, Verbrugghe J, Lamers I, Palmaers S, Timmermans A, Spooren A. Markerless motion capture systems as training device in neurological rehabilitation: a systematic review of their use, application, target population and efficacy. J Neuroeng Rehabil 2017 Dec 24;14(1):61. doi: 10.1186/s12984-017-0270-x
13. Lam WWT, Fong KNK. The application of markerless motion capture (MMC) technology in rehabilitation programs: a systematic review and meta-analysis. Virtual Real 2022 Sep 17; doi: 10.1007/s10055-022-00696-6
14. Mehdizadeh S, Faieghi M, Sabo A, Nabavi H, Mansfield A, Flint AJ, Taati B, Iaboni A. Gait changes over time in hospitalized older adults with advanced dementia: Predictors of mobility change. PLoS One 2021 Nov 17;16(11):e0259975. doi: 10.1371/journal.pone.0259975
15. Mehdizadeh S, Sabo A, Ng K-D, Mansfield A, Flint AJ, Taati B, Iaboni A. Predicting Short-Term Risk of Falls in a High-Risk Group With Dementia. J Am Med Dir Assoc 2021 Mar;22(3):689-695.e1. doi: 10.1016/j.jamda.2020.07.030
16. Ng K-D, Mehdizadeh S, Iaboni A, Mansfield A, Flint A, Taati B. Measuring Gait Variables Using Computer Vision to Assess Mobility and Fall Risk in Older Adults With Dementia. IEEE J Transl Eng Health Med 2020;8:1–9. doi: 10.1109/JTEHM.2020.2998326
17. Sabo A, Mehdizadeh S, Iaboni A, Taati B. Prediction of Parkinsonian Gait in Older Adults with Dementia using Joint Trajectories and Gait Features from 2D Video. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) IEEE; 2021. p. 5700–5703. doi: 10.1109/EMBC46164.2021.9630563
18. Sabo A, Mehdizadeh S, Iaboni A, Taati B. Estimating Parkinsonism Severity in Natural Gait Videos of Older Adults With Dementia. IEEE J Biomed Health Inform 2022 May;26(5):2288–2298. doi: 10.1109/JBHI.2022.3144917
19. Kondragunta J, Seidel R, Hirtz G. Machine learning based identification of elderly persons with cognitive impairment using dynamic time warping. Current Directions in Biomedical Engineering 2020 Sep 1;6(3):360–363. doi: 10.1515/cdbme-2020-3093
20. Graff MJL, Vernooij-Dassen MJM, Thijssen M, Dekker J, Hoefnagels WHL, Rikkert MGMO. Community based occupational therapy for patients with dementia and their care givers: randomised controlled trial. BMJ 2006 Dec 9;333(7580):1196. doi: 10.1136/bmj.39001.688843.BE
21. Suzuki T, Shimada H, Makizako H, Doi T, Yoshida D, Ito K, Shimokata H, Washimi Y, Endo H, Kato T. A Randomized Controlled Trial of Multicomponent Exercise in Older Adults with Mild Cognitive Impairment. PLoS One 2013 Apr 9;8(4):e61483. doi: 10.1371/journal.pone.0061483
22. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu

MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P, Moher D. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ BMJ Publishing Group Ltd; 2021;372. doi: 10.1136/bmj.n71

23. Specialist Unit for Review Evidence (SURE) 2018. Questions to assist with the critical appraisal of cross- sectional studies. Available at: http://www.cardiff.ac.uk/insrv/libraries/sure/checklists.html.
24. Sabo A, Mehdizadeh S, Ng KD, Iaboni A, Taati B. Assessment of Parkinsonian gait in older adults with dementia via human pose tracking in video data. J Neuroeng Rehabil 2020;17(1):97. doi: https://dx.doi.org/10.1186/s12984-020-00728-9
25. Seifallahi M, Hassani Mehraban A, Khamseh F, Salehi M, Hajati G, Khansari M, Ahmadzadeh M, Babaie M. Detection of mild cognitive Impairment from gait using Adaptive Neuro-Fuzzy Inference system. Biomed Signal Process Control 2022 Jan;71:103195. doi: 10.1016/j.bspc.2021.103195
26. Pedro AG, Kirsten H, Sebastian F, Kathrin J, Karsten W, Andreas H. Preliminary Viability Test of a 3-D-Consumer-Camera-Based System for Automatic Gait Feature Detection in People with and without Parkinson's Disease. 2020 IEEE International Conference on Healthcare Informatics, ICHI 2020 2020; doi: 10.1109/ICHI48887.2020.9374363
27. Tan D, Pua Y-H, Balakrishnan S, Scully A, Bower KJ, Prakash KM, Tan E-K, Chew J-S, Poh E, Tan S-B, Clark RA. Automated analysis of gait and modified timed up and go using the Microsoft Kinect in people with Parkinson's disease: associations with physical outcome measures. Med Biol Eng Comput 2019 Feb 20;57(2):369–377. doi: 10.1007/s11517-018-1868-2
28. Cimolin V, Vismara L, Ferraris C, Amprimo G, Pettiti G, Lopez R, Galli M, Cremascoli R, Sinagra S, Mauro A, Priano L. Computation of Gait Parameters in Post Stroke and Parkinson's Disease: A Comparative Study Using RGB-D Sensors and Optoelectronic Systems. Sensors (Basel) 2022;22(3). doi: https://dx.doi.org/10.3390/s22030824
29. Ospina BM, Chaparro JAV, Paredes JDA, Pino YJC, Navarro A, Orozco JL. Objective Arm Swing Analysis in Early-Stage Parkinson's Disease Using an RGB-D Camera (Kinect®)1. J Parkinsons Dis 2018 Oct 17;8(4):563–570. doi: 10.3233/JPD-181401
30. Ťupa O, Procházka A, Vyšata O, Schätz M, Mareš J, Vališ M, Mařík V. Motion tracking and gait feature estimation for recognising Parkinson's disease using MS Kinect. Biomed Eng Online 2015 Dec 24;14(1):97. doi: 10.1186/s12938-015-0092-7
31. Soltaninejad S, Rosales-Castellanos A, Ba F, Ibarra-Manzano MA, Cheng I. Body Movement Monitoring for Parkinson's Disease Patients Using A Smart Sensor Based Non-Invasive Technique. 2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom) IEEE; 2018. p. 1–6. doi: 10.1109/HealthCom.2018.8531197
32. Lai Y-R, Lien C-Y, Huang C-C, Lin W-C, Chen Y-S, Yu C-C, Cheng B-C, Kung C-T, Kung C-F, Chiang Y-F, Hung Y-T, Chang H-W, Lu C-H. Clinical Disease Severity Mediates the Relationship between Stride Length and Speed and the Risk of Falling in Parkinson's Disease. J Pers Med 2022 Jan 31;12(2):192. doi: 10.3390/jpm12020192
33. Muñoz-Ospina B, Alvarez-Garcia D, Clavijo-Moran HJC, Valderrama-Chaparro JA, García-Peña M, Herrán CA, Urcuqui CC, Navarro-Cadavid A, Orozco J. Machine Learning Classifiers to Evaluate Data From Gait Analysis With Depth Cameras in Patients With Parkinson's Disease. Front Hum Neurosci 2022 May 19;16. doi: 10.3389/fnhum.2022.826376
34. Otte K, Ellermeyer T, Vater T-S, Voigt M, Kroneberg D, Rasche L, Kruger T, Rohling HM, Kayser B, Mansow-Model S, Klostermann F, Brandt AU, Paul F, Lipp A, Schmitz-Hubsch T.

Instrumental Assessment of Stepping in Place Captures Clinically Relevant Motor Symptoms of Parkinson's Disease. Sensors (Basel) 2020;20(19). doi: https://dx.doi.org/10.3390/s20195465
35. Kaur R, Motl RW, Sowers R, Hernandez ME. A Vision-Based Framework for Predicting Multiple Sclerosis and Parkinson's Disease Gait Dysfunctions—A Deep Learning Approach. IEEE J Biomed Health Inform 2023 Jan;27(1):190–201. doi: 10.1109/JBHI.2022.3208077
36. Khan T, Zeeshan A, Dougherty M. A novel method for automatic classification of Parkinson gait severity using front-view video analysis. Technol Health Care 2021;29(4):643–653. doi: https://dx.doi.org/10.3233/THC-191960
37. Khan T, Westin J, Dougherty M. Motion cue analysis for Parkinsonian Gait Recognition. Open Biomedical Engineering Journal 2013;7(1):1–8. doi: https://dx.doi.org/10.2174/1874120701307010001
38. Li T, Chen J, Hu C, Ma Y, Wu Z, Wan W, Huang Y, Jia F, Gong C, Wan S, Li L. Automatic Timed Up-and-Go Sub-Task Segmentation for Parkinson's Disease Patients Using Video-Based Activity Classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2018 Nov;26(11):2189–2199. doi: 10.1109/TNSRE.2018.2875738
39. Morinan G, Peng Y, Rupprechter S, Weil RS, Leyland L-A, Foltynie T, Sibley K, Baig F, Morgante F, Gilron R, Wilt R, Starr P, O'Keeffe J. Computer-vision based method for quantifying rising from chair in Parkinson's disease patients. Intell Based Med 2022;6:100046. doi: 10.1016/j.ibmed.2021.100046
40. Rupprechter S, Morinan G, Peng Y, Foltynie T, Sibley K, Weil RS, Leyland L-A, Baig F, Morgante F, Gilron R, Wilt R, Starr P, Hauser RA, O'Keeffe J. A Clinically Interpretable Computer-Vision Based Method for Quantifying Gait in Parkinson's Disease. Sensors 2021 Aug 12;21(16):5437. doi: 10.3390/s21165437
41. Shin JH, Yu R, Ong JN, Lee CY, Jeon SH, Park H, Kim H-J, Lee J, Jeon B. Quantitative Gait Analysis Using a Pose-Estimation Algorithm with a Single 2D-Video of Parkinson's Disease Patients. J Parkinsons Dis 2021 Aug 2;11(3):1271–1283. doi: 10.3233/JPD-212544
42. Sabo A, Gorodetsky C, Fasano A, Iaboni A, Taati B. Concurrent Validity of Zeno Instrumented Walkway and Video-Based Gait Features in Adults With Parkinson's Disease. IEEE J Transl Eng Health Med 2022;10:1–11. doi: 10.1109/JTEHM.2022.3180231
43. Bridenbaugh SA, Kressig RW. Motor cognitive dual tasking. Z Gerontol Geriatr 2015 Jan 21;48(1):15–21. doi: 10.1007/s00391-014-0845-0
44. Montero-Odasso MM, Sarquis-Adamson Y, Speechley M, Borrie MJ, Hachinski VC, Wells J, Riccio PM, Schapira M, Sejdic E, Camicioli RM, Bartha R, McIlroy WE, Muir-Hunter S. Association of Dual-Task Gait With Incident Dementia in Mild Cognitive Impairment. JAMA Neurol 2017 Jul 1;74(7):857. doi: 10.1001/jamaneurol.2017.0643
45. Åhman HB, Cedervall Y, Kilander L, Giedraitis V, Berglund L, McKee KJ, Rosendahl E, Ingelsson M, Åberg AC. Dual-task tests discriminate between dementia, mild cognitive impairment, subjective cognitive impairment, and healthy controls – a cross-sectional cohort study. BMC Geriatr 2020 Dec 29;20(1):258. doi: 10.1186/s12877-020-01645-1
46. Procházka A, Vyšata O, Vališ M, Ťupa O, Schätz M, Mařík V. Use of the image and depth sensors of the Microsoft Kinect for the detection of gait disorders. Neural Comput Appl 2015 Oct 3;26(7):1621–1629. doi: 10.1007/s00521-015-1827-x
47. Ye M, Yang C, Stankovic V, Stankovic L, Cheng S. Gait phase classification for in-home gait assessment. 2017 IEEE International Conference on Multimedia and Expo (ICME) IEEE; 2017. p. 1524–1529. doi: 10.1109/ICME.2017.8019500