A Low-Cost Markerless motion capture system to automate Functional Gait Assessment: Feasibility Study

Osman Darici[1], Chanel Cabak[1], Jeremy D Wong[1,2]

Faculty of Kinesiology

Department of Biomedical Engineering

Abstract

Functional gait assessments in older adults have traditionally required manual in-person quantification of clinically-relevant metrics such as walking speed and step placement. This reliance on skilled labour hinders the frequency with which they are performed, and reduces their generalizability and replicability. To standardize and simplify gait assessments, we here leverage recently-developed open-source tools to produce a low-cost, AI driven markerless motion capture system. Validation of data collected with a traditional marker-based system on subjects (N=3) showed strong correlation to laboratory-standard measures of step length (R^2=0.989), step width (R^2=0.986), and body speed (R^2=0.964), suggesting that open-source markerless systems are currently sufficient to be used in gait assessments. Older adult subjects (N=5) performed the complete functional gaita assessment (FGA), and the system demonstrated data consistent with previous findings. Additional standard measurements were proposed to supplement and systematize existing FGA workflows. This markerless motion capture system demonstrates a proof-of-principle system for performing analyses of functional gait.

Introduction

Biomechanical analysis has largely been confined to laboratory settings, with limited application in practical environments such as clinics or rehabilitation. This is primarily due to the high cost of motion capture, and the complexity of data processing. Functional gait is an important indicator of overall health, and may provide critical information about fall risk. Falls in older adults are both prevalent and can dramatically reduce quality of life [1–3], and incur an estimated ~$10.3 billion per year in Canada[2] and $50 billion in the USA[3]. To address the current lack of standardization and ease-of use, we leverage recently-developed open-source tools to demonstrate the feasibility of a low-cost, AI driven markerless motion capture system to assess functional gait.

Three dimensional (3D) motion-capture is often of limited use in a clinical setting because it consumes money for equipment and ongoing software licensing, requires substantial time and expertise to analyse, and yet yields a large dataset that is difficult to convert into useful metrics that can predict health. Traditionally, high-frequency motion capture cameras are placed in a dedicated lab space to encircle the subject and record the position of limbs. Most commonly, limb position has been inferred from markers placed on the skin to track limb segments, a process which requires substantial skill, and consumes on the order of 30-60 min per subject. Following calibration of cameras to optimally estimate their positions, the set of 2D images recorded from cameras around the room are combined (often via proprietary software) to render a 3D motion capture. The recorded marker positions are not necessarily consistent through time, and must be “cleaned” to interpolate through dropped frames, or corrected for erroneous marker swaps. Recently, Markerless laboratory systems have begun to be used and have comparable accuracy, but at no major reduction in cost[4,5] due to software licensing. Present 3D motion capture systems thus have yet to achieve a widespread adoption because of prohibitive cost and analytical time.

A cost-effective motion capture system could make older adult functional gait assessments routine, quantifiable, and comparable, by standardizing existing clinical assessments. Here we highlight three established testing methods to show the difficulties in making assessments routine. Current

approaches assess the functional level of gait and balance by collecting simple movement lateral step placements, walking duration, and walking speed. Timed Up and Go (TUG)[6], Functional Gait Assessment (FGA)[7], The Edinburgh Visual Gait Score (EVGS)[8], have been developed to monitor gait for clinical decision making and fall risk prediction. TUG and FGA do not require any sophisticated equipment, but the resulting quantification is then more subjective: task time for each is measured frequently via stop-watch, requiring trained personnel and limiting comparability. Moreover, FGA identifies reduction in functional gait In FGA, lateral step placements constitute the remaining assessment data, and are assessed by visual identification, again requiring training and limiting across-subject and across-appointment comparability. EVGS outputs more sophisticated gait metrics such as joint angles, but requires time to process[8] still depends on the observer's decision, may lack of inter-rater reliability[9,10], and may not be predictive. These methods reflect the constraints of performing quantitative assessments within a clinical setting. An affordable and simple end-to-end motion capture system that quantifies gait metrics across these tests would reduce clinician bias, save assessment time, simplify clinician workflow, and provide comparable data. In this paper we focus on the Functional gait assessment, although we believe our approach is generalizable.

Advances in artificial intelligence and computer vision led to accurate pose estimation and markerless motion capture techniques [11–14] that are opensource and present the possibility of motion capture for a few hundred dollars. In this study, we tested the feasibility of one of these systems to assess young and old adults performing tasks of FGA[15]. Utilizing only 3 low-cost webcams, we measured motion data and found comparable accuracy to a marker-based motion capture system. This set-up is capable of measuring step length and width, and step speed, and thereby obviate the need for these measures to be performed by a clinician. We believe that this set-up can easily be adapted for clinics in performing assessments, and reduce the subjective bias of the user to provide sufficiently accurate gait parameters.

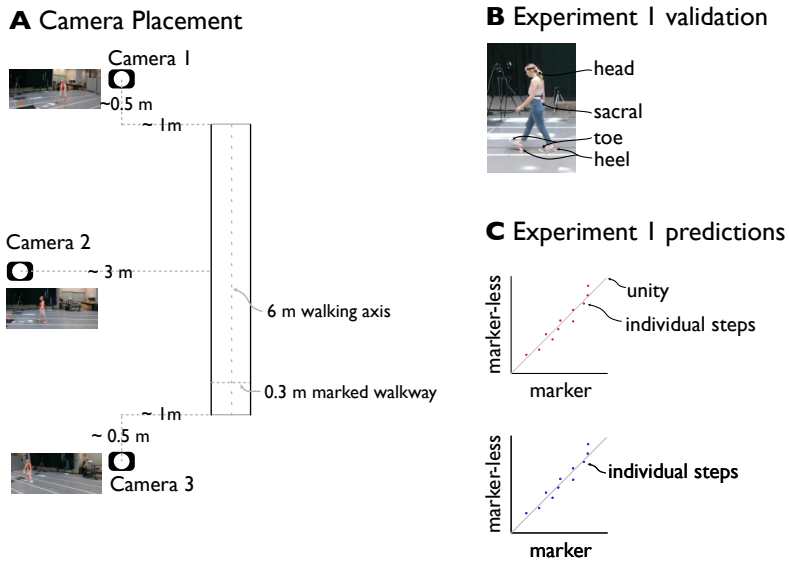


Figure 1: Experimental setup and validation experiment. A: Camera placement, with approximate distances relative to the left edge of the walkway. B: Experimental validation of step placements, using markers placed on the feet, sacrum and head. C: Validation of markerless data: step length, width and walking speed.

Methods

Ethics

Older adult subjects (N=5) provided their written informed consent according to institutional review board procedures.

Design

We first established the validity of using an opensource markerless motion capture system (Freemocap)[15] to record clinically-relevant metrics from walking—namely those used in FGA, 1) movement time; and 2) step width and step length—by comparing markerless foot placement position and the resulting step times and durations, to those from an active optical motion capture system commonly used in biomechanical studies (Phasespace Inc.). Next, we performed Functional Gait Assessment on young adult controls and Older adults[16]. We placed the analysis code in a repository for use by practitioners interested in performing their own analysis.

Setup

The markerless motion capture system used 3 (Jetaku Inc; Amazon) web cameras placed laterally to the main 6m walking axis (Figure 1A). As a demonstration of feasibility, a medium performance desktop PC (2018; 3.4 GHz; 4 Cores; 16 GB Ram) was used to record and process data. Total added cost of the cameras and usb extension cables was less than $200 (CAD).

The beginning of experiment session before recording data required approximately 20 minutes of time to setup cameras and perform 1) calibration and 2) capture volume orientation. To calibrate the system, the markerless motion capture system optimally estimates the 3D position of web cameras, and accounts for visual distortion of the camera optics. This is done by simultaneously recording video data from a Charuco board—a single black-and-white calibration image with known checkerboard pattern and dimension. To accommodate a 6m walking area, a large poster of dimensions (square size: 15.7 cm) was used. Custom software optimizes the 3D position of the cameras to minimize the 3D-positional error of the detected checkerboard patterns (or "bundle adjustment[17]"). The software[15] reports the number of full boards detected from each camera, and provides some information about calibration accuracy; practically, we ensured that at least 400 boards were recorded for from each of the web cameras for each of our recording sessions. This calibration process took 2 minutes of Charuco positioning, and about 10 minutes of computer processing time. Note that this calibration process needs to be done only once per camera configuration; stationary camera positions, such as those securely anchored without potential for repositioning, might only require one calibration.

To perform capture volume orientation, subjects stood at the beginning of the walkway and then at 5m, and 1 m right of the walkway. This procedure performed two functions. It defined the plane of the walking area, allowing rotation of the recorded data to interpretable dimensions. Additionally, the known magnitude of these 5m and 1m distances, while typically within about 5% of the true distances, were used to linearly rescale movements uniformly from the origin.

During data processing, keypoint software estimates the position of joints and other points of interest on the body (Google Mediapipe). The software performs a lowpass filter (25 Hz) to reduce the effect of joint misestimation, motion blur, and other artefacts.

Experiment 1

We performed our first experiment to determine the validity of the markerless motion capture system to compute three measures that are necessary and sufficient to automate FGA: step length, step width, and walking speed. To determine the accuracy of computer vision methods, we used marker-based motion capture and collected 6 markers per person to capture feet, torso, and head position. We simultaneously recorded walking trials of a 4 m distance with both systems, under two conditions: normal step width, and step width where subjects were asked to step on the edge of the 30 cm marked path.

We compared the estimated positions of the two systems by using the heel marker position from the markered system to the foot position from markerless motion capture. We time-aligned the two systems by determining the maximum cross-correlation between the two extracted walking bouts after upsampling the markerless system (30Hz) to the markered system's framerate (240 Hz). We subtracted the initial (T=0) position of each left foot to register the two systems at the beginning of the walking bout.

We computed step length and width as the distance between two consecutive foot placements. We defined body speed as the distance between consecutive midstance events divided by the change in time.

Experiment 2

Older adult subjects (N=5; mean age: 83 years) were asked to perform a complete functional gait assessment, and timed up and go. We performed three repetitions of each task.

Markerless Setup

Accurate detection of body segments is sensitive to visual elements that make it difficult for the Mediapipe algorithm to clearly separate body keypoints from the background. Moreover, illumination—which affects shutter speed and thus motion blur—can affect localization. Optimal algorithm performance was achieved by using contrasting shoes with the ground colour—either white or dark shoes against the grey floor—and similarly contrasting colours for clothing, that fit relatively tight to the body. These adjustments can substantially affect the algorithm's tracking accuracy substantially, and occasionally performed poorly despite reasonable contrast, which we speculate may be related to particular aspects of the motion being absent from the training set. Therefore, we found it important that body keypoints be checked once after normal walking to determine that tracking of the feet and head were accurate.

Data analysis

We developed custom Matlab code to analyze walking bouts, focusing on the metrics used in Functional Gait Assessment: namely step length, step width, foot placement, and walking speed. Briefly, the software extracts a bout of walking gait from kinematic data by detecting initiation and termination events using cross-correlation of a template of foot speed during initiation and

termination of gait. To identify step placements during the bout, foot speed was low-pass filtered at 3 Hz, and regions where footspeed was below the speed threshold of 0.15 m/s were identified as stance regions. We compute

To analyze gait bouts, we first identified the initiation of each walking sequence by cross-correlating the start of each bout with a predefined gait initiation template created from the sum of left and right foot speed. This approach allowed us to accurately segment individual walking sequences across trials.

Foot placement data were processed by applying a low-pass filter at 3 Hz to the speed of each foot. Using this filtered signal, we identified midstance as the midpoint of a region where foot speed remained below 0.15 m/s, indicating the foot was securely on the ground. Step timing was subsequently calculated based on the interval between consecutive midstance points, allowing for accurate determination of step durations across each trial.

Head speed was used to estimate walking speed. Tracked head position was lowpass filtered (4th order, 5Hz cutoff).

A specific area of difficulty with Mediapipe is its identification of foot location, which can occasionally give erroneous foot velocities that show simultaneous acceleration of the left and right feet during midstance. This problem may be exacerbated by poor lighting conditions which increase motion blur. While foot position during static positions, such as stance, is typically well-localized, foot motion can be misestimated. Because our trials exclusively involved walking and not running, we determined simultaneous acceleration was an artifact rather than a genuine movement, and performed an interpolation correction on the foot trajectories whenever sections of data displayed simultaneous foot accelerations exceeding 7.5 m/s^2.

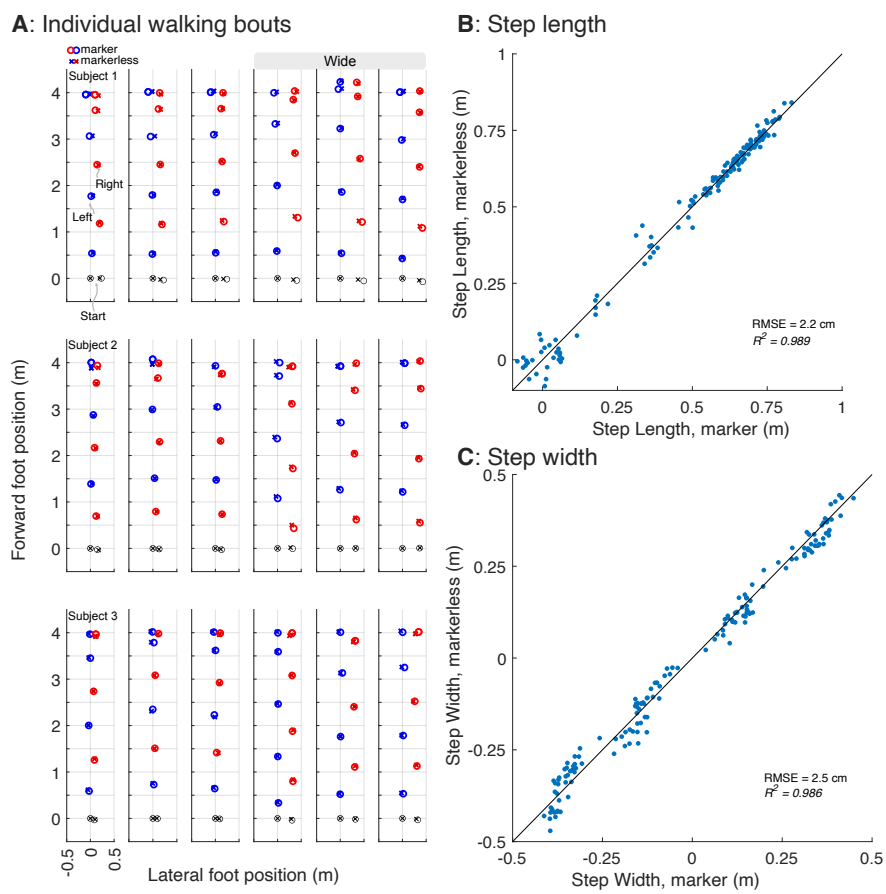


Figure 2: Comparison of markerless system foot placement estimates with traditional marker-based motion capture. A: individual steps identified via marker (O's) and markerless motion capture (X's). B: Step length measures for individual steps. C: Step width.

We fit walking speed data to power-law predictions of human

walking, under the assumption that older adults minimize the energetic cost to a combination of energetic cost and linear time[18].

Results

Experiment 1

The markerless motion capture system was accurate in its detection of foot placement events (Figure 2A). The Markerless foot positions showed good agreement with the marker-based motion capture, demonstrating high correlation in step length (R^2=0.989; Figure 2B) and step width (R^2=0.986; Figure 2C).

Body speed measures with the markerless system were also similar to marker-based motion capture. Figure 3 depicts step speed across trials (Figure 3; R^2 = 0.964).

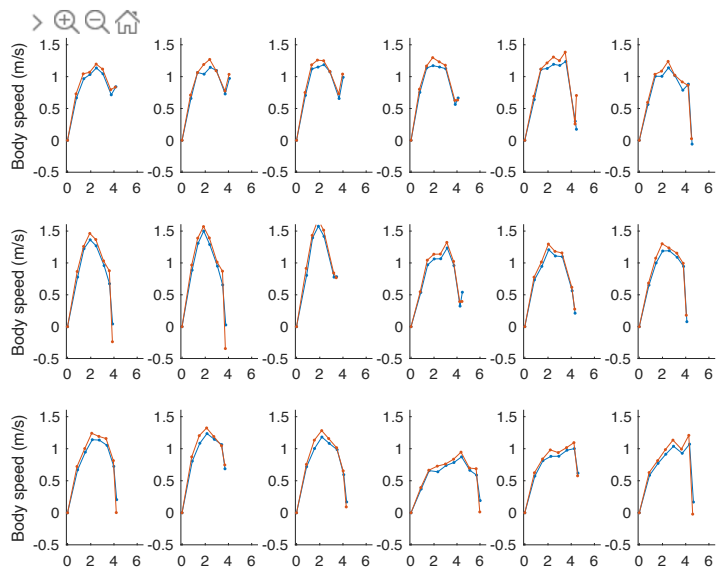


Figure 3: Body speed comparison of marker-based (blue) and marker-less (red) foot steps.

Experiment 2

In Experiment 2, we employed the Functional Gait Assessment (FGA) for our older adult subjects, which resulted in quantification of individual footsteps (Figure 4A). Head speed (Figure 4A, bottom) was sufficient to show deviations in walking speed (speed projected along the walking axis) for the FGA trials, relative to nominal preferred walking (Trial 1).

Across subjects and repetitions, performance variability was evident, with significant fluctuations in maximum lateral step placement (Figure 4B, top). While rarely did subjects exhibit different FGA classifications on successful repetitions (denoted by horizontal black dotted lines), substantial variability is apparent.

Measures in addition to FGA that could be additionally used—step width, walking duration—were qualitatively similar to FGA measures.

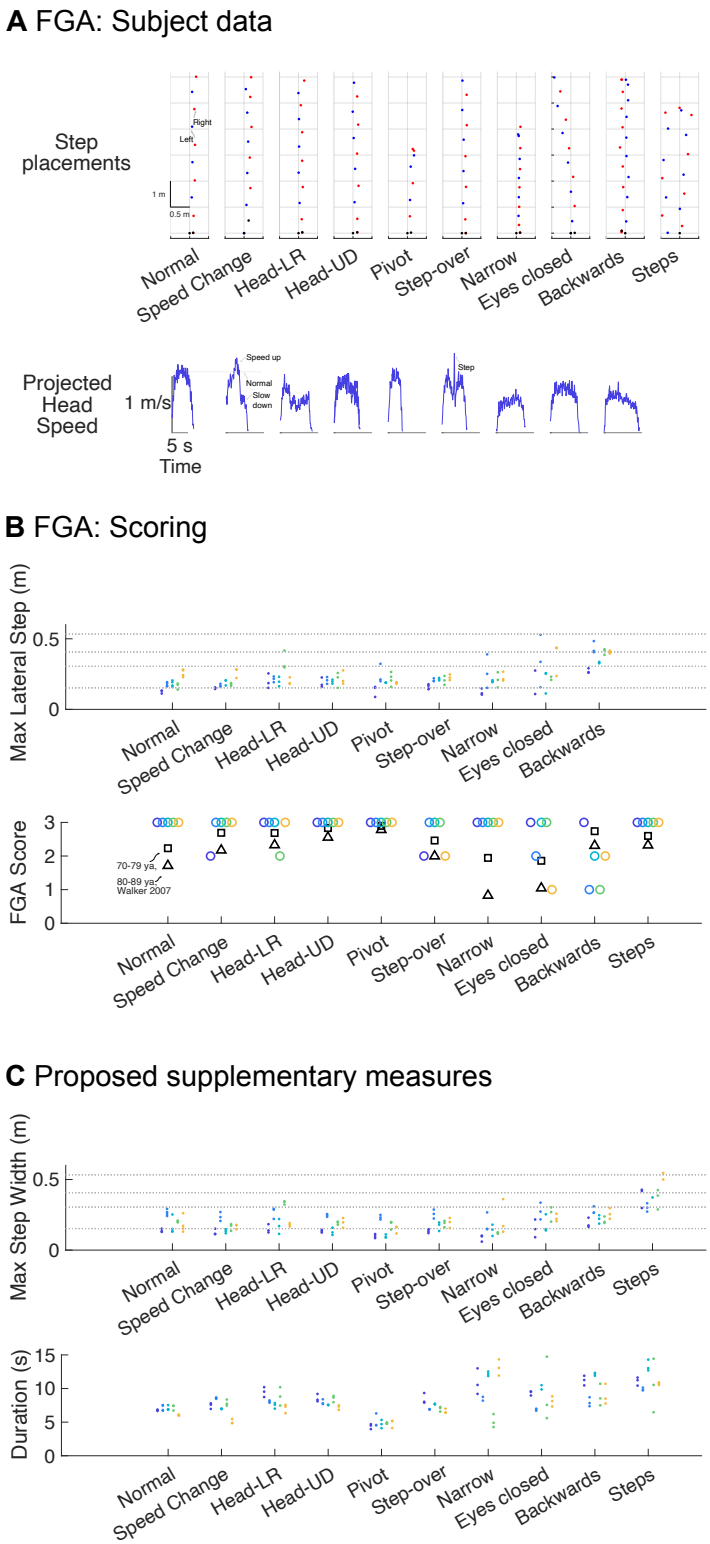


Figure 4: Functional Gait Assessment. A: Individual subject data. B: Functional Gait assessment scoring. Maximum lateral step placement for all FGA trials, across subjects (except for Steps trial). Data for mean aged subject groups adapted Walker 2007. C: Proposed additional measures of step width and movement duration.

Discussion

This study demonstrated the feasibility of a low-cost, AI-driven motion capture system utilizing three standard web-cameras. The total cost of the added cameras and usb-extension cables is less than $200 CAD. The computer was inexpensive and performance issues may especially be avoided in the case where data are collected with a lightweight client program, and returned to a server for processing. Through experiments on young and older adults, we showed that this system could accurately capture foot trajectories in an absolute reference frame, achieving a comparable level of accuracy for step width and step length to a gold-standard 10-camera motion capture system. Furthermore, the system's utility was tested through Functional Gait Assessment (FGA) and provided suitable data comparable to previous data[19].

The low-cost system exhibited strong agreement with laboratory standard, marker-based in measuring step length and step width, and walking speed, which are useful predictors for functional gait (Figures 4, 5, 6). These data currently form the foundation of clinical assessments, and here we review the rationale behind recording these measures. Step width is particularly significant for maintaining lateral stability[20–24], especially given the instability of human gait in the frontal plane[25]. Step length varies with walking speed[26,27] and the speed deteriorates with age[28]. Therefore, it may be essential to track step length for assessing gait, particularly during unsteady walking conditions like accelerating, decelerating, or changing directions where step length and stride length do not show the same trends. Traditional systems for measuring step length and width, such as motion capture systems or floor mats, are often costly and require technical expertise for data analysis. Our low-cost system offers a viable, efficient alternative, delivering accurate measurements that can directly benefit clinicians. We also propose the use of step width, in addition to or in place of lateral excursion, which is not sensitive to details of the walkway and provides information about lateral stability comparable to a substantial existing scientific literature.

A major contribution of this system is to reduce the subjective nature and burden of manual determination of lateral step placement. We believe an automated markerless approach is surprisingly robust and obviates the need for a clinician to carefully attend each step. Our system successfully captured foot step placements during FGA. We measured step widths with very high R^2, and RMSE of approximately 2cm. Lateral foot placement is an important metric in FGA, such that the clinician should visually detect how far a foot moved away out of given limits (12 feet wide walkway). The capability of measuring foot trajectories enabled quantifying lateral foot placement and as well as the condition time (the duration that it takes to finish a condition i.e. walking straight) and therefore automated scoring of FGA (FGA is based on scores of how fast a subject finishes a condition and how far they get out of a 12 foot wide walk way within the condition), reducing the reliance on subjective visual assessments by clinicians. This functionality reduces clinician workload as well and increases the precision of gait assessments.

Our system also yields simple automated assessments of gait speed and walking duration. Gait speed is a crucial metric in fall risk assessment and traditional approaches often involve single speed measurements over set distances, relying on manual timing by clinician. This process is repeated multiple times to see the deviations or deterioration (if any) in gait speed. Furthermore, gait speed is combined with other measures such as trunk or head acceleration variability or stride length variability and used to predict fall risk. Our system allows for a more detailed analysis by capturing

speed trajectories over varying distances and conditions, such as those in FGA tests (particularly change in gait speed condition, Figure 6) as opposed to single speed measurement. Metrics like peak speed, mean speed, acceleration, and deceleration durations can be quantified from the trajectories. Therefore, our system can offer new metrics of speed for assessing gait speed changes and fall risk. Furthermore, these metrics can be compared with optimal control models that predict speed and provide foundations about the difference between older and young adults.

One limitation of the existing markerless system is the potential for motion of each foot to influence the keypoint detection location of the other. Occasionally this results in positional artifacts such that the stationary foot is briefly detected to move towards the swing foot as it crosses the stance leg. We suspect that these errors likely stem from the underlying Mediapipe detection, since several different open-source software packages, despite substantial differences in preprocessing and computer-vision approaches, when utilizing the same backend keypoint detection of Mediapipe, display the same artefacts[15,29]. Efforts to address these issues, such as using distinct footwear or shorts, yielded limited improvement. Despite this, the system demonstrated high accuracy during foot-flat (stance) phases, and filtering can substantially address the mistaken estimate of stance-leg motion, making it reliable for FGA.

Future work will focus on enhancing the system's capabilities and usability. This includes increasing the number or quality of webcams to extend coverage and reduce foot-tracking artifacts. We plan to develop a user-friendly application interface that a healthcare professional can easily use to perform gait assessments, such as FGA and TUG, and generate scores and illustrative graphs with just a few button clicks. We also intend to keep patient records to support longitudinal tracking of gait metrics, facilitating progress monitoring.

We also plan to explore integrating inertial measurement units (IMU's) with the motion capture system. Combining data from IMU's mounted on the feet (measuring linear acceleration and rotational velocity of the feet) can enhance the motion capture accuracy by correcting foot crossing artifacts and extending the effective capture range. Another future objective is to position motion capture cameras to cover extended distances and use them for position correction of IMU measurements. When a subject walks their feet, movement can be measured with IMU's[30,31], but absolute orientation and location errors from accelerometer drift may enlarge quickly in time. These errors can be mitigated with our motion capture system. These open-source approaches demonstrate the feasibility of much larger capture volumes and perhaps multiple simultaneous subject recordings. For instance, assuming two cameras are sufficient to record an area of 2 meters by 2 meters, then 10 cameras might be integrated to cover a large real-world coordinate system, and provide body position data across a large functional region. Whenever the feet are in camera visibility, the system can output real world feet position from the cameras, and these data could be integrated into IMU position estimates (wider than what the motion capture system covers), and may include realistic, poorly understood movements including turning and obstacle avoidance. This setup may significantly improve the usage of IMU's and can facilitate various experiments to investigate how individuals navigate and control their step length, width, and speed in larger environments.

In conclusion, this study validated the feasibility of a low-cost motion capture system powered by AI and webcams. With continued development, this system has the potential to transform clinical gait assessments by providing precise, automated measurements of key metrics such as step width and

speed. It offers a cost-effective solution to reduce clinician workload, minimize bias, and enhance the accuracy of gait examinations, making advanced gait analysis accessible to a broader range of healthcare settings.

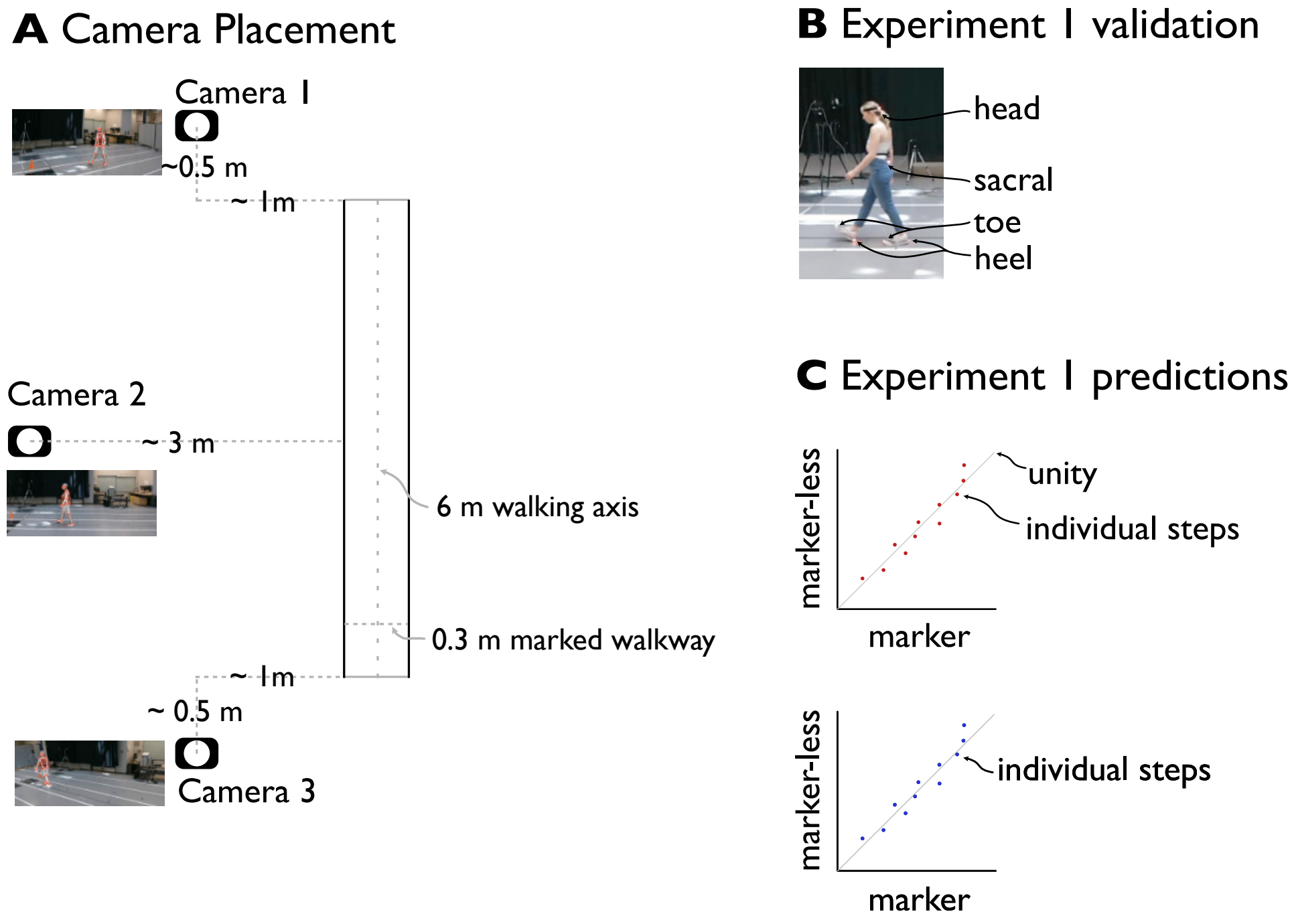
References

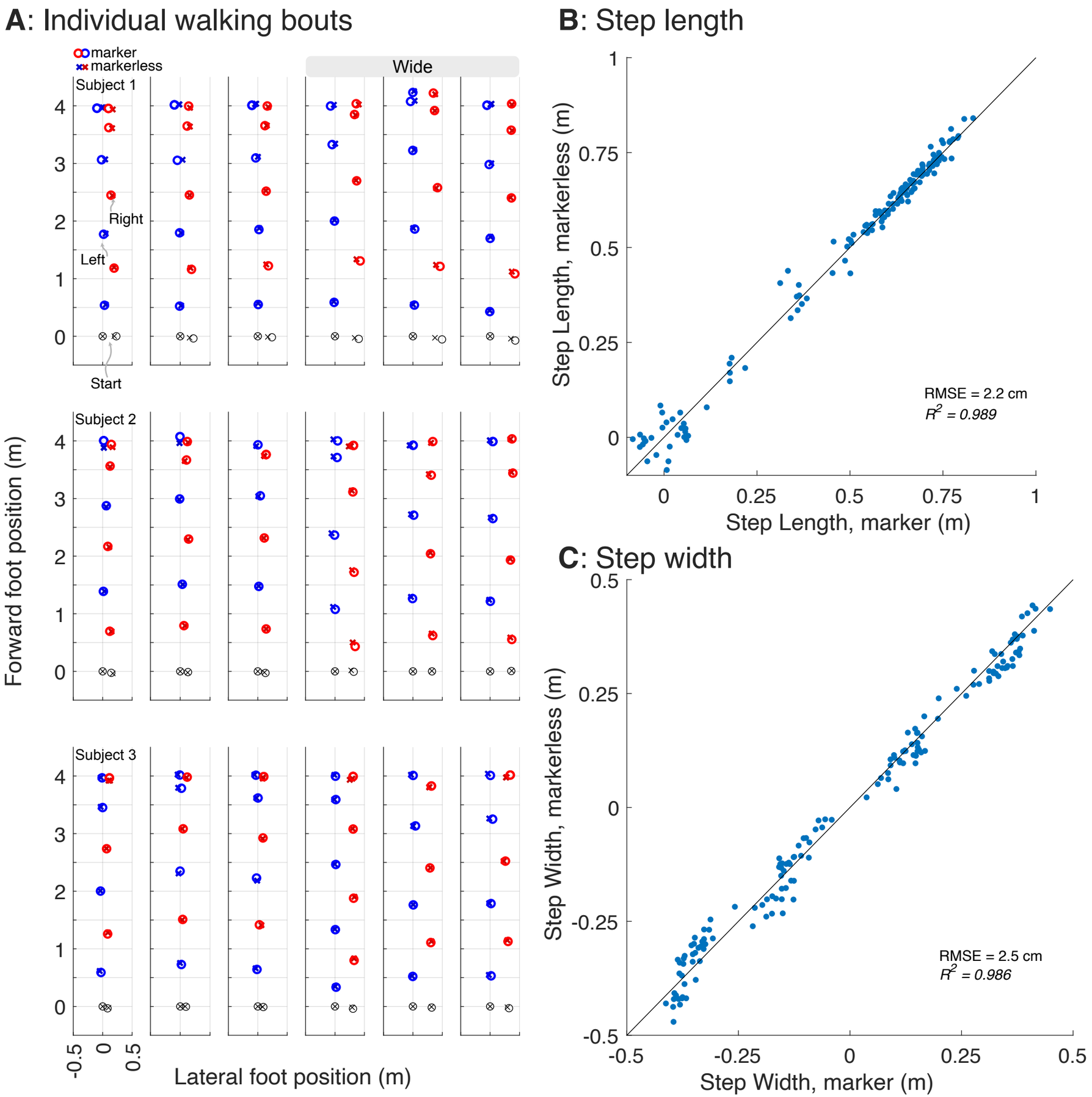
1. CDC. About Older Adult Fall Prevention. *Older Adult Fall Prevention* https://www.cdc.gov/falls/about/index.html (2024).
2. Cost of Injury in Canada – Parachute. https://parachute.ca/en/professional-resource/cost-of-injury-in-canada/.
3. Kakara, R. Nonfatal and Fatal Falls Among Adults Aged ≥65 Years — United States, 2020–2021. *MMWR Morb. Mortal. Wkly. Rep.* **72**, (2023).
4. Lichtwark, G. A., Schuster, R. W., Kelly, L. A., Trost, S. G. & Bialkowski, A. Markerless motion capture provides accurate predictions of ground reaction forces across a range of movement tasks. *J. Biomech.* **166**, 112051 (2024).
5. Nakano, N. *et al.* Evaluation of 3D markerless motion capture accuracy using OpenPose with multiple video cameras. *Front. Sports Act. Living* **2**, 50 (2020).
6. Herman, T., Giladi, N. & Hausdorff, J. M. Properties of the 'Timed Up and Go' Test: More than Meets the Eye. *Gerontology* **57**, 203–210 (2011).
7. Wrisley, D. M. & Kumar, N. A. Functional gait assessment: concurrent, discriminative, and predictive validity in community-dwelling older adults. *Phys. Ther.* **90**, 761–773 (2010).
8. Aroojis, A., Sagade, B. & Chand, S. Usability and Reliability of the Edinburgh Visual Gait Score in Children with Spastic Cerebral Palsy Using Smartphone Slow-Motion Video Technology and a Motion Analysis Application: A Pilot Study. *Indian J. Orthop.* **55**, 931 (2021).

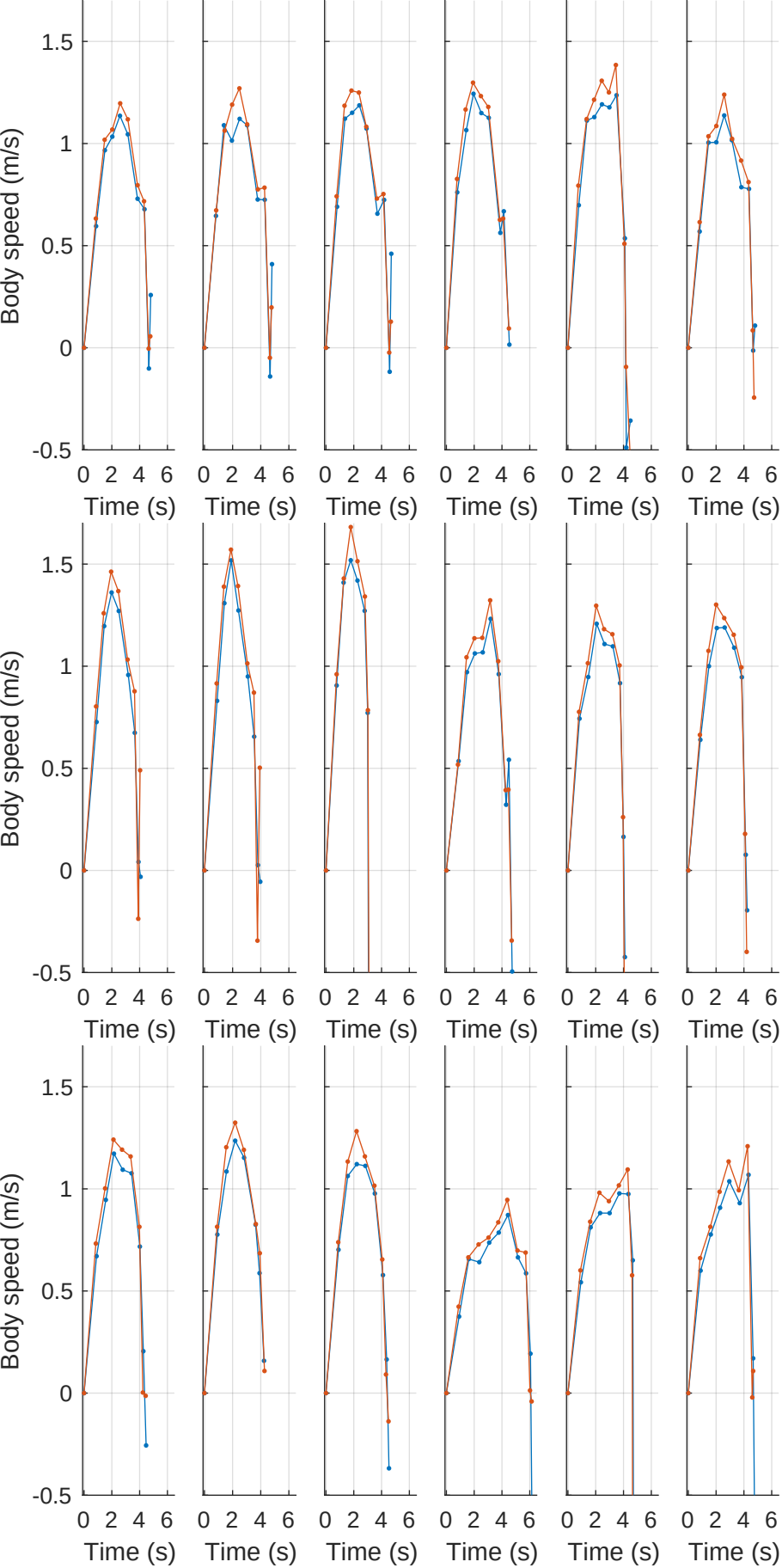
9. Ong, A. M. L., Hillman, S. J. & Robb, J. E. Reliability and validity of the Edinburgh Visual Gait Score for cerebral palsy when used by inexperienced observers. *Gait Posture* **28**, 323–326 (2008).
10. Viehweger, E. *et al.* Influence of clinical and gait analysis experience on reliability of observational gait analysis (Edinburgh Gait Score Reliability). *Ann. Phys. Rehabil. Med.* **53**, 535–546 (2010).
11. Ramesh, S. H., Lemaire, E. D., Tu, A., Cheung, K. & Baddour, N. Automated Implementation of the Edinburgh Visual Gait Score (EVGS) Using OpenPose and Handheld Smartphone Video. *Sensors* **23**, 4839 (2023).
12. Guo, Y., Liu, J., Li, G., Mai, L. & Dong, H. Fast and Flexible Human Pose Estimation with HyperPose. Preprint at https://doi.org/10.48550/arXiv.2108.11826 (2022).
13. Graving, J. M. *et al.* DeepPoseKit, a software toolkit for fast and robust animal pose estimation using deep learning. *eLife* **8**, e47994 (2019).
14. Cao, Z., Hidalgo, G., Simon, T., Wei, S.-E. & Sheikh, Y. OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. Preprint at https://doi.org/10.48550/arXiv.1812.08008 (2019).
15. Matthis, J., Cherian, A. & Wirth, T. The FreeMoCap Project-and-Gaze/Hand coupling during a combined three-ball juggling and balance task. *J. Vis.* **22**, 4195–4195 (2022).
16. Wrisley, D. M. & Kumar, N. A. Functional gait assessment: concurrent, discriminative, and predictive validity in community-dwelling older adults. *Phys. Ther.* **90**, 761–773 (2010).
17. Karashchuk, P. *et al.* Anipose: A toolkit for robust markerless 3D pose estimation. *Cell Rep.* **36**, (2021).
18. Wong, J. D. & Kuo, A. D. Energy and time optimization unify the control of reaching and walking. in *Society for Neuroscience* (Washington, D.C., 2023).

19. Walker, M. L. *et al.* Reference group data for the functional gait assessment. *Phys. Ther.* **87**, 1468–1477 (2007).
20. Kuo, A. D. Stabilization of lateral motion in passive dynamic walking. *Int. J. Robot. Res.* **18**, 917–930 (1999).
21. Donelan, J. M., Kram, R. & Kuo, A. D. Mechanical and metabolic determinants of the preferred step width in human walking. *Proc. R. Soc. Lond. B Biol Sci* **268**, 1985–92 (2001).
22. Wang, Y. & Srinivasan, M. Stepping in the direction of the fall: the next foot placement can be predicted from current upper body state in steady-state walking. *Biol. Lett.* **10**, 20140405 (2014).
23. Townsend, M. A. Biped gait stabilization via foot placement. *J. Biomech.* **18**, 21–38 (1985).
24. Redfern, M. S. & Schumann, T. A model of foot placement during gait. *J. Biomech.* **27**, 1339–1346 (1994).
25. Collins, S., Ruina, A., Tedrake, R. & Wisse, M. Efficient bipedal robots based on passive-dynamic walkers. *Science* **307**, 1082–1085 (2005).
26. Kuo, A. D. A simple model of bipedal walking predicts the preferred speed-step length relationship. *J. Biomech. Eng.* **123**, 264–269 (2001).
27. Grieve, D. W. Gait patterns and the speed of walking. *Bio-Med Engng* **3**, 119–122 (1968).
28. Middleton, A., Fritz, S. L. & Lusardi, M. Walking speed: The functional vital sign. *J. Aging Phys. Act.* **23**, 314–322 (2015).
29. Prible, D. Caliscope: GUI Based Multicamera Calibration and MotionTracking. *J. Open-source Softw.* **9**, 7155 (2024).
30. Carlisle, R. E. & Kuo, A. D. Optimization of energy and time predicts dynamic speeds for human walking. *eLife* **12**, e81939 (2023).

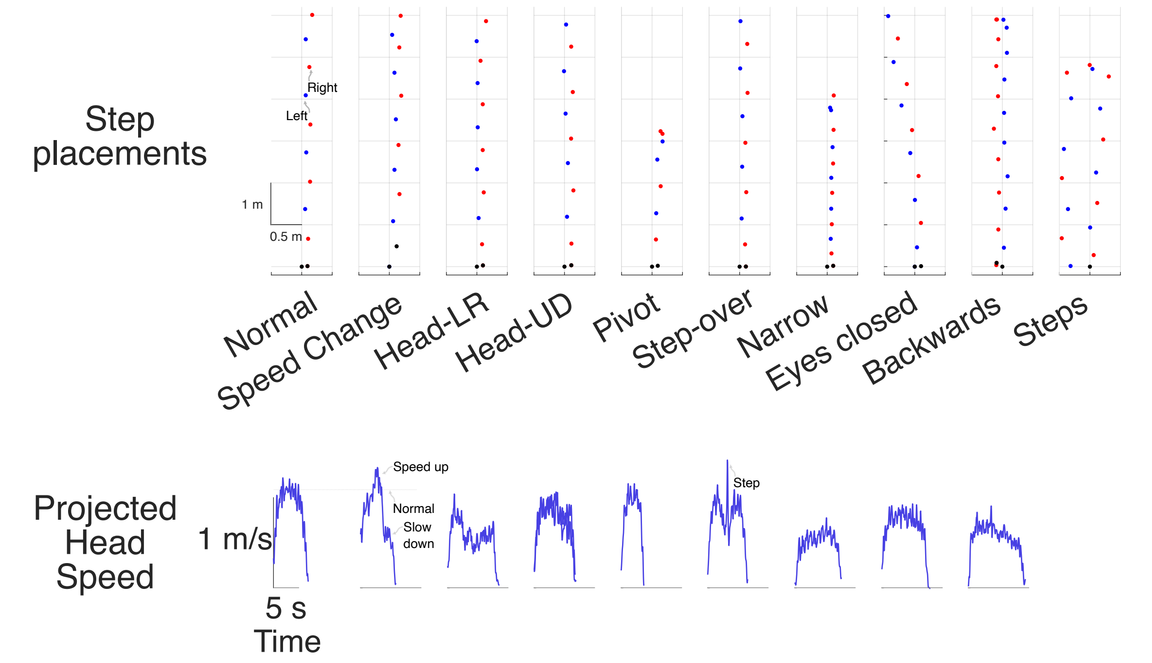
31. Darici, O. & Kuo, A. D. Humans optimally anticipate and compensate for an uneven step during walking. *eLife* **11**, e65402 (2022).


A Camera Placement
Camera 1
~0.5 m
~ 1m
Camera 2
~ 3 m
6 m walking axis
0.3 m marked walkway
~ 1m
~ 0.5 m
Camera 3
B Experiment 1 validation
head
sacral
toe
heel
C Experiment 1 predictions
marker-less
marker
unity
individual steps
marker-less
marker
individual steps

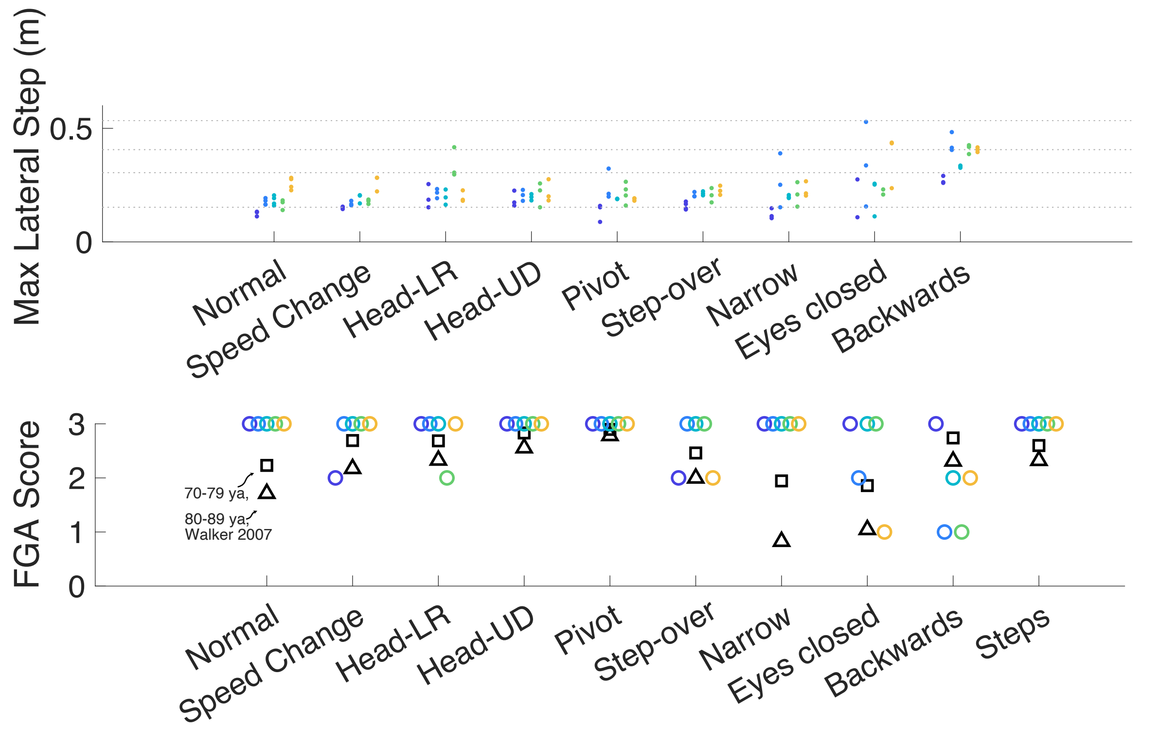
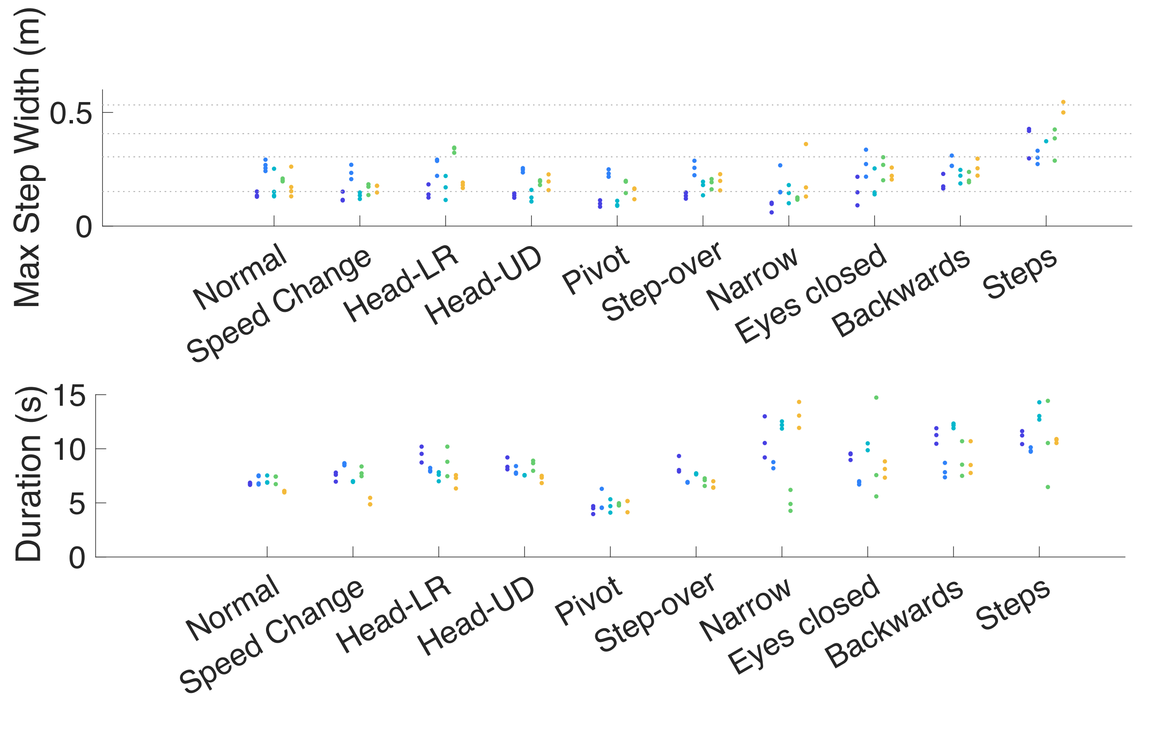

A: Individual walking bouts
marker
markerless
Wide
Subject 1
Subject 2
Subject 3
Right
Left
Start
Forward foot position (m)
Lateral foot position (m)
B: Step length
Step Length, markerless (m)
Step Length, marker (m)
RMSE = 2.2 cm
R2 = 0.989
C: Step width
Step Width, markerless (m)
Step Width, marker (m)
RMSE = 2.5 cm
R2 = 0.986


Body speed (m/s)
1.5
1
0.5
0
-0.5
0 2 4 6
Time (s)

A FGA: Subject data



B FGA: Scoring



C Proposed supplementary measures