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[1]

Department of Biomedical Engineering[1,2]

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 individuals trained in motion analysis 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 with custom analysis for Functional Gait Assessment, using 3 Cameras. 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=0.98), step width (R^2=0.97), and head speed (R^2=0.95), suggesting that open-source markerless systems are sufficient to be used in gait assessments. The markerless system demonstrated data similar to previous FGA findings in older adult subjects (N=5). Supplemental measurements are proposed that augment existing FGA workflows with standard biomechanical gait measures Step Width, walking Duration, and continuous Gait Speed. This markerless motion capture system demonstrates a proof-of-principle system for performing analyses of functional gait.

Introduction

Despite considerable potential utility, an automated biomechanical analysis of a person's walking gait currently lacks widespread use. The value of gait assessments are both as an indicator of overall health, and an assessment of mobility and associated gait risks. Walking speed, for example, has been shown to be as predictive of an older adult's health as blood pressure (Middleton et al., 2015). Step width—which increases with age (Dean et al., 2007; Maki, 1997; Owings and Grabiner, 2004a, 2004b; Schrager et al., 2008)—is thought to predict a person's potential for loss of balance, or compensation for instability (Brach et al., 2005; Dean et al., 2007; Gabell and Nayak, 1984; Skiadopoulos et al., 2020). The societal impacts on open access to assessment could be dramatic. The risk of falls increases with age such that by age 70, 50% in adults will experience a fall annually. Falls in older adults can dramatically reduce quality of life, with ~24,000 older adults being hospitalized each year in Canada due to fall related hip fractures and this incurring an estimated ~$10.3 billion per year in Canada, and $50 billion in the USA (Canada, 2024; "Cost of Injury in Canada – Parachute," 2021; Kakara, 2023). Increasing the degree of automation in the recording and analysis of gait has the potential to lead to gait assessments that are performed more frequently, and with greater repeatability and comparability, and is the focus of this study.

One obstacle to gait analysis is the complexity and cost in analyzing walking behaviour. Motion capture data—the most widely accepted method for analysis of full-body locomotion—requires costly equipment to collect, substantial time to analyze, and skill to convert kinematic data into clinically relevant gait metrics. Dedicated spaces are often used to allow a set of cameras to encircle a subject. Markers placed on limb segments consume substantial experiment time, and cameras must be correctly calibrated to convert 2D images recorded from cameras to into 3D positions. Recently, Markerless laboratory systems have begun to be used. These systems eliminate the use of markers at comparable accuracy (Lichtwark et al., 2024; Nakano et al., 2020), but remain primarily accessible only to research institutions due to costs of software licensing, while the operational costs of analysis are still considerable.

Standard clinical tests tend to rely on visual inspection by the clinician and may be sensitive to inter-clinician variability and bias. This is true for the Functional Gait Assessment (FGA) (Wrisley and Kumar, 2010), Timed Up and Go (Herman et al., 2011), and Edinburgh Visual Gait Score (Aroojis et al., 2021), each of which are different protocols meant to monitor gait for clinical decision making and fall risk prediction. FGA does not require sophisticated equipment, but the resulting quantification requires the following to be monitored across 10 different gait trials: task time is recorded via stopwatch; lateral step placements by monitoring step footfalls on a marked floor; and trial-specific gait details such speed changes (task 2), response time (task 5), and step height over obstacles (task 6). Several conditions require subjective judgments such as whether a speed change was “significant” or “minor”. The Timed Up-and-Go test requires total duration of a 3m out-and-back walk, from a seated start to end. The Edinburgh Visual Gait Score outputs more sophisticated gait metrics such as joint angles, but requires (in addition to an attentive clinician) substantial processing time (Aroojis et al., 2021), and still may lack of inter-rater reliability (Ong et al., 2008; Viehweger et al., 2010).

These clinical tests, designed to be easy to perform by clinicians and care-givers, may be less comparable to the general field of gait biomechanics. Mediolateral foot placement, for example—used in FGA—is arguably easier to measure but the biomechanically-relevant measure is step width. Also, timed movement duration is a simple estimate of average gait speed, but continuous measurement of gait speed –across distance, and task—may be more informative (Carlisle and Kuo, 2023). In this paper we focus on testing feasibility of increasing automation of the Functional Gait Assessment, while also augmenting the assessment with measurements common to gait biomechanics—such as step width and gait speed trajectories. Our approach generalizes to the automation of other clinical tasks as well, and is thus extensible.

Advances in AI-driven computer vision have led to accurate pose estimation and markerless motion capture techniques (Cao et al., 2019; Graving et al., 2019; Guo et al., 2022; Ramesh et al., 2023) that are open-source. In this study, we tested the feasibility of one of these systems, The FreeMoCap Project (Matthis et al., 2022), to correctly report key gait metrics, and perform FGA. Utilizing 3 consumer-grade web-cameras, we measured motion data and found comparable accuracy to a marker-based motion capture system. We therefore tested the prediction that an automated system could reliably detect step lengths and widths and perform FGAs on older adult subjects.

Methods

Ethics

Young (N=3) and older adult subjects (N=5; ages 65-79) provided their written informed consent according to institutional review board procedures.

Experimental Designs

We performed two experiments. First we established the validity of the opensource markerless motion capture system (FreeMoCap: Matthis et al., 2022) to record clinically-relevant metrics—step width, step length, and walking speed—by comparing markerless foot placement 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 Older adults (Wrisley and Kumar, 2010). We placed the analysis code in a repository for use by practitioners interested in performing their own analysis.

Methods

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).

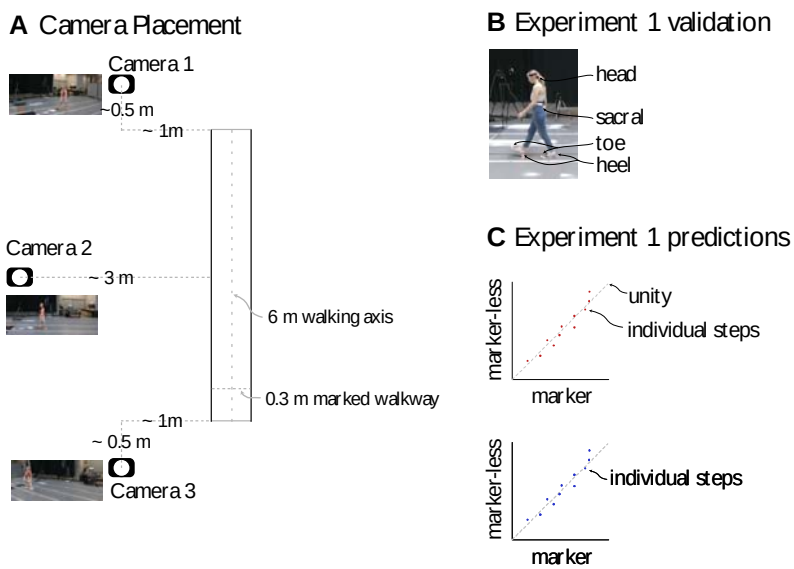


Figure 1: Experimental setup and validation experiment. A: Camera placement, with approximate distances relative to the left edge of the walkway. B: Experimental validation of step placements, using markers placed on the feet, sacrum and head. C: Validation of markerless data: step length, width and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

Experiment sessions required approximately 20 minutes of preparation time to 1) physically set-up cameras, 2) perform calibration and 3) 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 that FGA requires, a large poster (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 (Karashchuk et al., 2021)”). The software (Matthis et al., 2022) 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 board positioning, and about 10 minutes of compute. To perform capture volume orientation, subjects stood in three locations to define a simple coordinate system: 1) at the beginning of the walkway; 2) at +5m (forward) along the pathway; and 3) at 1 m right of the walkway. This procedure defined the plane of the walking area, allowing rotation of the recorded data to interpretable dimensions. It also allowed us to correct for any bias in the calibration, as

these known magnitudes of 5m and 1m distances could be used to rescale data collected along each axis. Typically, FreeMoCap's calibration procedure resulted in approximately a 5% error in absolute estimate of walkway length.

During data processing, key-point software makes estimates of 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: Validation

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 of subjects (N=3). We simultaneously recorded walking trials of a 4 m distance with both systems, under two conditions: normal step width, and a 'wide' condition where subjects were asked to step on the edge of the 30 cm marked path. We performed three replications of each.

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 up-sampling the markerless system (30 Hz) 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 measured head speed as the motion of the head marker (located centrally in the back of the head via headband), and for the markerless system we defined it as the average of the left ear, right ear, and nose keypoints.

Experiment 2: FGA

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

Markerless Setup: lighting and clothing

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 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 for Functional Gait Assessment: primarily step length, step width, foot placement, and walking speed. A walking gait is detected from kinematic data using cross-correlation. This process uses a template foot speed trajectory during initiation and termination of gait, each of which are cross-correlated to the foot speed of a subject's trial, to identify when a walk has started and ended. 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. The average of that stance region was taken as the step location. 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, 5 Hz cutoff).

Because our trials exclusively involved walking and not running, our algorithm detected if simultaneous acceleration of both feet occurred, and linear interpolated foot marker positions during any such periods (acceleration threshold: 7.5 m/s^2).

FGA Scores: Automation

Currently FGA provides a scoring rubric using a combination of lateral step variability and speed thresholds, the definition of which is sometimes not definitive. For example, FGA Scores for Condition 2: "Change in Gait Speed" requires the clinician to decide whether a person has achieved "significant" or only "minor" speed changes; FGA Scores for Conditions 3 and 4 (head movement trials) require "no change in gait" for the peak functional score (Wrisley and Kumar, 2010). In our FGA scores, we defined the following levels to quantify these adjectives as proof of principle of assessment automation (and thus, any arbitrary settings may be adjusted at a clinician's discretion):

- Condition 2: *Gait Speed Change*:
    - FGA 3: speed change greater than 125% normal speed
    - FGA 2: speed change between [110%, 125%] normal speed
    - FGA 1: speed change between [105%, 110%] normal speed
    - FGA 0: no speed increase greater than 105% of normal
- Conditions 3 and 4*: Gait with Horizontal/Vertical head turns*:
    - FGA 3: no speed or deviation change
    - FGA 2: no speed change, mediolateral foot placements as noted in (Wrisley and Kumar, 2010)
    - FGA 1: speed change to less than 90% normal speed
    - FGA 0: speed change less than 75% normal speed
- In Condition 5: *Gait And Pivot Turn*:
    - FGA 3: turning in less than 3 s
    - FGA 2: turning (cued verbally at 2m into walk) took longer than 3 s
    - FGA 1: turning (cued verbally at 2m into walk) took longer than 4.5 s
    - FGA 0: incomplete
- In Condition 6: *Step Over Obstacle:*
    - FGA 3: high obstacle clearance, speed greater than 75% normal

- FGA 2: lower obstacle, speed greater than 75% of normal
- FGA 1: lower obstacle, speed less than 75% of normal
- FGA 0: incomplete

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 during both normal and wide step widths, demonstrating high correlation in step length (R^2=0.98; Figure 2B) and step width for both normal and wide trials (R^2=0.97; Figure 2C).

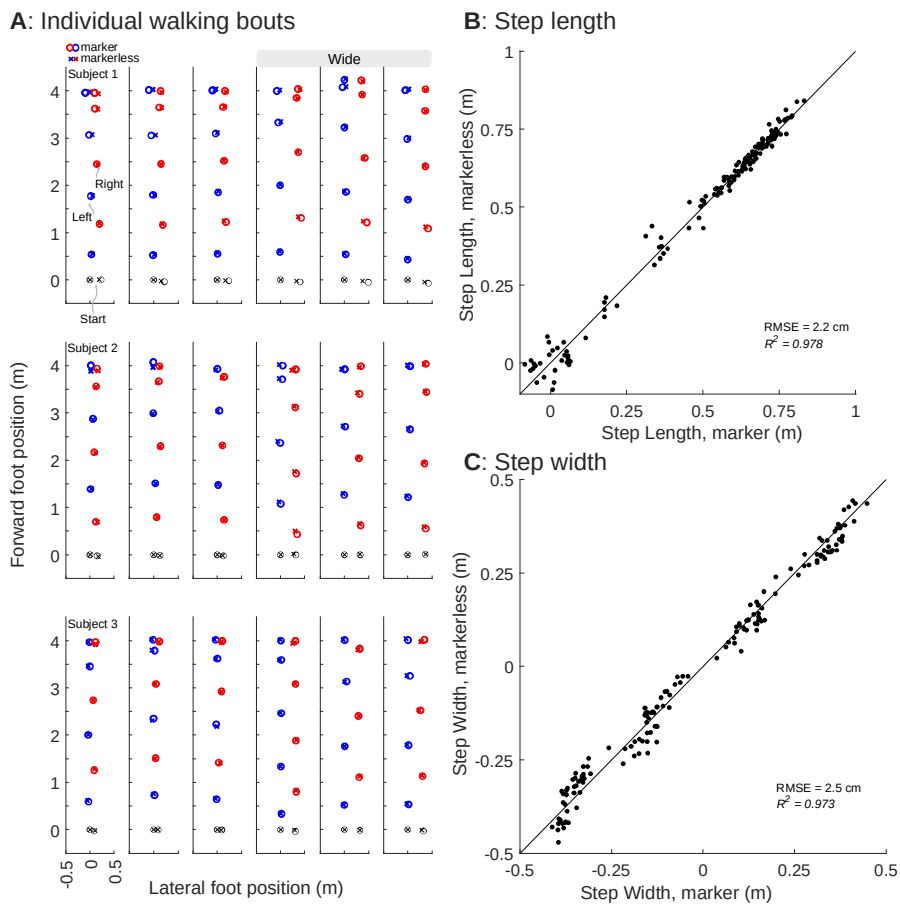


Figure 2: Comparison of markerless system foot placement estimates with traditional marker-based motion capture. A: individual steps of all subjects of both normal and wide walking trials identified via marker (O's) and markerless motion capture (X's). B and C: Step length (B) and width (C; negative is left-to-right step width) for each step shown in A.

Head speed measures with the markerless system were also similar to marker-based motion capture. Figure 3 depicts step speed across the normal and wide trials (Figure 3; R^2 = 0.91 to 0.98; mean = 0.95).

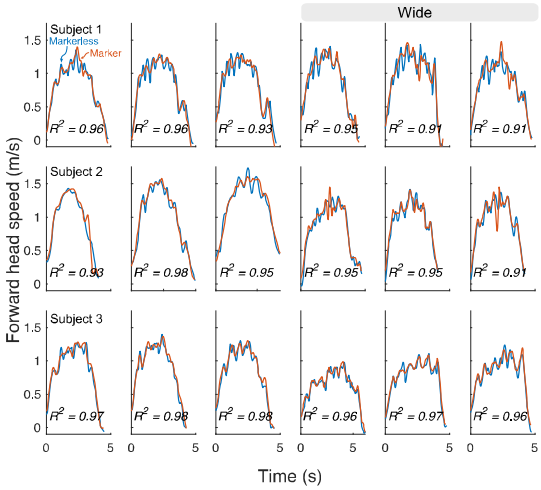


Figure 3: Head speed measured during walking trials, by markerless (blue) and marker-based (red) methods.

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.

Supplementary measures (Figure 4C) such as movement duration and step width (both median and maximum) were readily and appear broadly consistent across trials.

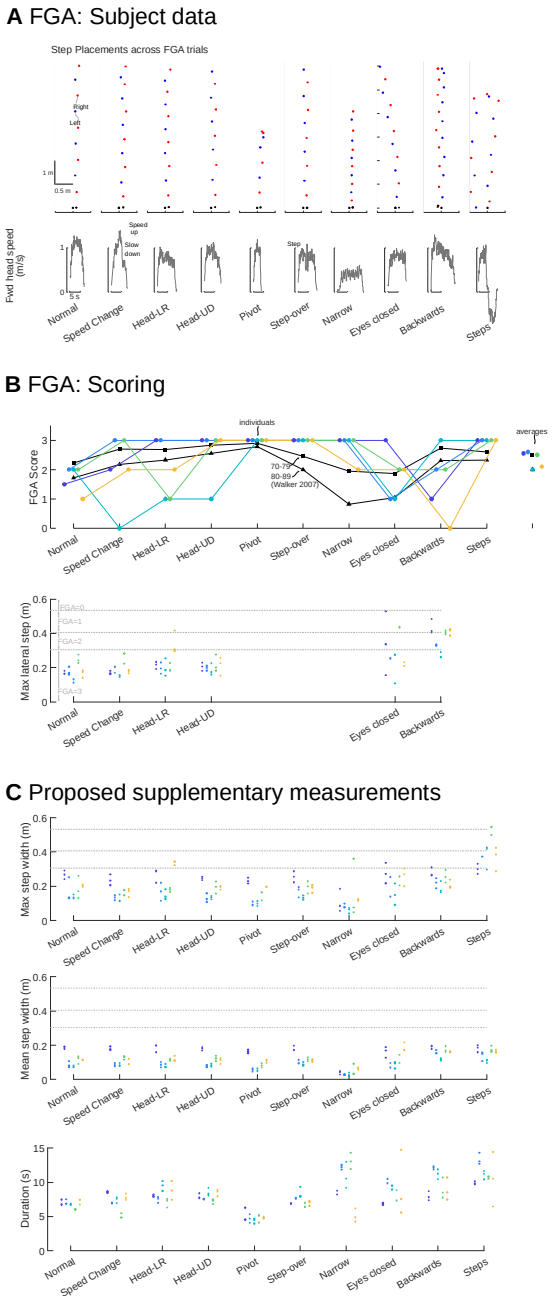


Figure 4: Functional Gait Assessment. A: Representative subject data, step placements for left (blue) and right (red) feet for all conditions. B: Top: Functional Gait assessment scores for all subjects, ordered in ascending age (65, 65, 67,71,79); data for mean aged subject groups adapted Walker 2007 for 70-79 (squares) and 80-90 (triangles). Bottom: Maximum lateral step placement for all 6 FGA trials that depend on lateral step. C: Proposed additional measures of step width and movement duration, applicable to all trials.

Discussion

This study demonstrated the feasibility of a low-cost, AI-driven motion capture system to perform functional gait assessment. 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. Furthermore, the system's utility was tested through Functional Gait Assessment (FGA) and provided suitable data comparable to previous data (Walker et al., 2007). The total cost of the three added consumer-grade web cameras and USB-extension cables was less than $200 CAD, and the analysis computer was inexpensive, meaning an existing computer at a clinic should be sufficient. Thus, modern open-source software appears ready to enable step-length, width and gait speed clinical testing for between 10% and 1% the cost of standard laboratory-based systems.

A critical question of markerless motion-capture systems is whether they are accurate enough for a given real-world application. Keypoint detection inference models vary in 1) outputs: the set of points that are returned; 2) inputs the training set used to generate the model, in this case, human movements; and 3) details of model implementation, such as model architecture, training, and hyperparameters. Here we show that a system leveraging Google’s Mediapipe keypoint detection algorithm had sufficient foot position accuracy during stance phases to produce adequate step lengths and widths. Velocity information from head speed was also sufficient for walking tasks. Moreover, we expect the quality of available, open-source inference models to only improve, as new models continue to be developed worldwide (Chen et al., 2019; Nath et al., 2019). Thus, the potential for applications to health and industry will likely broaden.

Functional gait assessment relies heavily on human visual identification of foot placement (Figure 4). The related gait measurement, step width, is important for maintaining lateral stability (Bruijn and van Dieën, 2018; Donelan et al., 2001; Kuo, 1999; Redfern and Schumann, 1994; Townsend, 1985; Wang and Srinivasan, 2014), given the instability of human gait in the frontal plane (Collins et al., 2005). Step length varies with walking speed (Grieve, 1968; Kuo, 2001) and gait speed decreases with age (Middleton et al., 2015). Continuous monitoring of both frontal and lateral steps may be particularly useful during unsteady walking conditions like accelerating, decelerating, or changing directions. Other stride-based techniques such as inertial measurement units are incapable of measuring step length and width, and thus have limited use for automatic scoring. Here we propose to use step width in addition to or in place of mediolateral foot placement (Figure 4C). It is widely used in the existing scientific literature (Donelan et al., 2001; Kuo, 1999; Redfern and Schumann, 1994; Townsend, 1985; Wang and Srinivasan, 2014), applies to non-straight walking paths, and thus is a more flexible measure of balance control.

Our system also yields simple automated assessments of gait speed. Gait speed is a crucial metric in fall risk assessment and traditional approaches often involve only average speed measurements over set distances, relying on manual timing by clinician. This process is repeated multiple times to observe 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 4) as opposed to single speed measurement. Metrics like peak speed, mean speed, acceleration, and deceleration durations could 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 (Carlisle and Kuo, 2023; Darici and Kuo, 2023, 2022) that

predict speed and may provide testable mechanistic explanations underlying the difference between older and young adults.

One potential use for markerless motion capture is to integrate inertial measurement units (IMUs). Combining data from IMUs mounted on the feet (measuring linear acceleration and rotational velocity of the feet) can enhance the motion capture accuracy. Under normal conditions, movement can be measured with IMUs (Carlisle and Kuo, 2023; Darici and Kuo, 2022), but absolute orientation and location errors from accelerometer drift enlarge quickly in time without registration. Much larger capture volumes and perhaps multiple simultaneous subject recordings may also be realized with a combined setup. For instance, assuming two cameras are sufficient to record an area of 2 meters by 2 meters, 10 cameras might be integrated to cover a large real-world coordinate system and provide body position data across a large functional region. This setup may significantly improve the usage of IMUs and can facilitate various experiments to investigate how individuals navigate and control their step length, width, and speed in larger environments.

This study validated the feasibility of a low-cost motion capture system powered by computer vision and web cameras. 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.

Acknowledgments

This research was supported by NSERC Discovery (Wong), the University of Calgary Catalyst (Wong), and Biomedical Engineering Summer Student Scholarship (Cabak).

Figure legends

Figure 5: 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.

Figure 2: Comparison of markerless system foot placement estimates with traditional marker-based motion capture. A: individual steps of all subjects of both normal and wide walking trials identified via marker (O's) and markerless motion capture (X's). B and C: Step length (B) and width (C; negative is left-to-right step width) for each step shown in A.

Figure 3: Head speed measured during walking trials, by markerless (blue) and marker-based (red) methods.

Figure 4: Functional Gait Assessment. A: Representative subject data, step placements for left (blue) and right (red) feet for all conditions. B: Top: Functional Gait assessment scores for all subjects, ordered in ascending age (65, 65, 67,71,79); data for mean aged subject groups adapted Walker 2007 for 70-79 (squares) and 80-90 (triangles). Bottom: Maximum lateral step placement for all 6 FGA trials that depend on lateral step. C: Proposed additional measures of step width and movement duration, applicable to all trials.

References

Aroojis, A., Sagade, B., Chand, S., 2021. 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. https://doi.org/10.1007/s43465-020-00332-y

Brach, J.S., Berlin, J.E., VanSwearingen, J.M., Newman, A.B., Studenski, S.A., 2005. Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed. J. Neuroengineering Rehabil. 2, 21. https://doi.org/10.1186/1743-0003-2-21

Bruijn, S.M., van Dieën, J.H., 2018. Control of human gait stability through foot placement. J. R. Soc. Interface 15, 20170816. https://doi.org/10.1098/rsif.2017.0816

Canada, P.H.A. of, 2024. Surveillance report on falls among older adults in Canada [WWW Document]. URL https://www.canada.ca/en/public-health/services/publications/healthy-living/surveillance-report-falls-older-adults-canada.html (accessed 10.25.24).

Cao, Z., Hidalgo, G., Simon, T., Wei, S.-E., Sheikh, Y., 2019. OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. https://doi.org/10.48550/arXiv.1812.08008

Carlisle, R.E., Kuo, A.D., 2023. Optimization of energy and time predicts dynamic speeds for human walking. eLife 12, e81939. https://doi.org/10.7554/eLife.81939

Chen, K., Wang, Jiaqi, Pang, J., Cao, Y., Xiong, Y., Li, X., Sun, S., Feng, W., Liu, Z., Xu, J., Zhang, Z., Cheng, D., Zhu, C., Cheng, T., Zhao, Q., Li, B., Lu, X., Zhu, R., Wu, Y., Dai, J., Wang, Jingdong, Shi, J., Ouyang, W., Loy, C.C., Lin, D., 2019. MMDetection: Open MMLab Detection Toolbox and Benchmark. https://doi.org/10.48550/arXiv.1906.07155

Collins, S., Ruina, A., Tedrake, R., Wisse, M., 2005. Efficient bipedal robots based on passive-dynamic walkers. Science 307, 1082–1085. https://doi.org/10.1126/science.1107799

Cost of Injury in Canada – Parachute [WWW Document], 2021. URL https://parachute.ca/en/professional-resource/cost-of-injury-in-canada/ (accessed 10.25.24).

Darici, O., Kuo, A.D., 2023. Humans plan for the near future to walk economically on uneven terrain. Proc. Natl. Acad. Sci. 120, e2211405120. https://doi.org/10.1073/pnas.2211405120

Darici, O., Kuo, A.D., 2022. Humans optimally anticipate and compensate for an uneven step during walking. eLife 11, e65402. https://doi.org/10.7554/eLife.65402

Dean, J.C., Alexander, N.B., Kuo, A.D., 2007. The Effect of Lateral Stabilization on Walking in Young and Old Adults. IEEE Trans. Biomed. Eng. 54, 1919–1926. https://doi.org/10.1109/TBME.2007.901031

Donelan, J.M., Kram, R., Kuo, A.D., 2001. Mechanical and metabolic determinants of the preferred step width in human walking. Proc. R. Soc. Lond. B Biol Sci 268, 1985–92.

Gabell, A., Nayak, U.S.L., 1984. The Effect of Age on Variability in Gait. J. Gerontol. 39, 662–666. https://doi.org/10.1093/geronj/39.6.662

Graving, J.M., Chae, D., Naik, H., Li, L., Koger, B., Costelloe, B.R., Couzin, I.D., 2019. DeepPoseKit, a software toolkit for fast and robust animal pose estimation using deep learning. eLife 8, e47994. https://doi.org/10.7554/eLife.47994

Grieve, D.W., 1968. Gait patterns and the speed of walking. Bio-Med Engng 3, 119–122.

Guo, Y., Liu, J., Li, G., Mai, L., Dong, H., 2022. Fast and Flexible Human Pose Estimation with HyperPose. https://doi.org/10.48550/arXiv.2108.11826

Herman, T., Giladi, N., Hausdorff, J.M., 2011. Properties of the ‘Timed Up and Go’ Test: More than Meets the Eye. Gerontology 57, 203–210. https://doi.org/10.1159/000314963

Kakara, R., 2023. Nonfatal and Fatal Falls Among Adults Aged ≥65 Years — United States, 2020–2021. MMWR Morb. Mortal. Wkly. Rep. 72. https://doi.org/10.15585/mmwr.mm7235a1

Karashchuk, P., Rupp, K.L., Dickinson, E.S., Walling-Bell, S., Sanders, E., Azim, E., Brunton, B.W., Tuthill, J.C., 2021. Anipose: A toolkit for robust markerless 3D pose estimation. Cell Rep. 36.

Kuo, A.D., 2001. A simple model of bipedal walking predicts the preferred speed-step length relationship. J. Biomech. Eng. 123, 264–269.

Kuo, A.D., 1999. Stabilization of lateral motion in passive dynamic walking. Int. J. Robot. Res. 18, 917–930.

Lichtwark, G.A., Schuster, R.W., Kelly, L.A., Trost, S.G., Bialkowski, A., 2024. Markerless motion capture provides accurate predictions of ground reaction forces across a range of movement tasks. J. Biomech. 166, 112051. https://doi.org/10.1016/j.jbiomech.2024.112051

Maki, B.E., 1997. Gait changes in older adults: predictors of falls or indicators of fear. J Am Geriatr Soc 45, 313–320.

Matthis, J., Cherian, A., Wirth, T., 2022. The FreeMoCap Project-and-Gaze/Hand coupling during a combined three-ball juggling and balance task. J. Vis. 22, 4195–4195.

Middleton, A., Fritz, S.L., Lusardi, M., 2015. Walking speed: The functional vital sign. J. Aging Phys. Act. 23, 314–322. https://doi.org/10.1123/japa.2013-0236

Nakano, N., Sakura, T., Ueda, K., Omura, L., Kimura, A., Iino, Y., Fukashiro, S., Yoshioka, S., 2020. Evaluation of 3D markerless motion capture accuracy using OpenPose with multiple video cameras. Front. Sports Act. Living 2, 50.

Nath, T., Mathis, A., Chen, A.C., Patel, A., Bethge, M., Mathis, M.W., 2019. Using DeepLabCut for 3D markerless pose estimation across species and behaviors. Nat. Protoc. 14, 2152–2176.

Ong, A.M.L., Hillman, S.J., Robb, J.E., 2008. Reliability and validity of the Edinburgh Visual Gait Score for cerebral palsy when used by inexperienced observers. Gait Posture 28, 323–326. https://doi.org/10.1016/j.gaitpost.2008.01.008

Owings, T.M., Grabiner, M.D., 2004a. Variability of step kinematics in young and older adults. Gait Posture 20, 26–29. https://doi.org/10.1016/S0966-6362(03)00088-2

Owings, T.M., Grabiner, M.D., 2004b. Step width variability, but not step length variability or step time variability, discriminates gait of healthy young and older adults during treadmill locomotion. J. Biomech. 37, 935–938. https://doi.org/10.1016/j.jbiomech.2003.11.012

Ramesh, S.H., Lemaire, E.D., Tu, A., Cheung, K., Baddour, N., 2023. Automated Implementation of the Edinburgh Visual Gait Score (EVGS) Using OpenPose and Handheld Smartphone Video. Sensors 23, 4839. https://doi.org/10.3390/s23104839

Redfern, M.S., Schumann, T., 1994. A model of foot placement during gait. J. Biomech. 27, 1339–1346.

Schrager, M.A., Kelly, V.E., Price, R., Ferrucci, L., Shumway-Cook, A., 2008. The effects of age on medio-lateral stability during normal and narrow base walking. Gait Posture 28, 466–471.

Skiadopoulos, A., Moore, E.E., Sayles, H.R., Schmid, K.K., Stergiou, N., 2020. Step width variability as a discriminator of age-related gait changes. J. NeuroEngineering Rehabil. 17, 41. https://doi.org/10.1186/s12984-020-00671-9

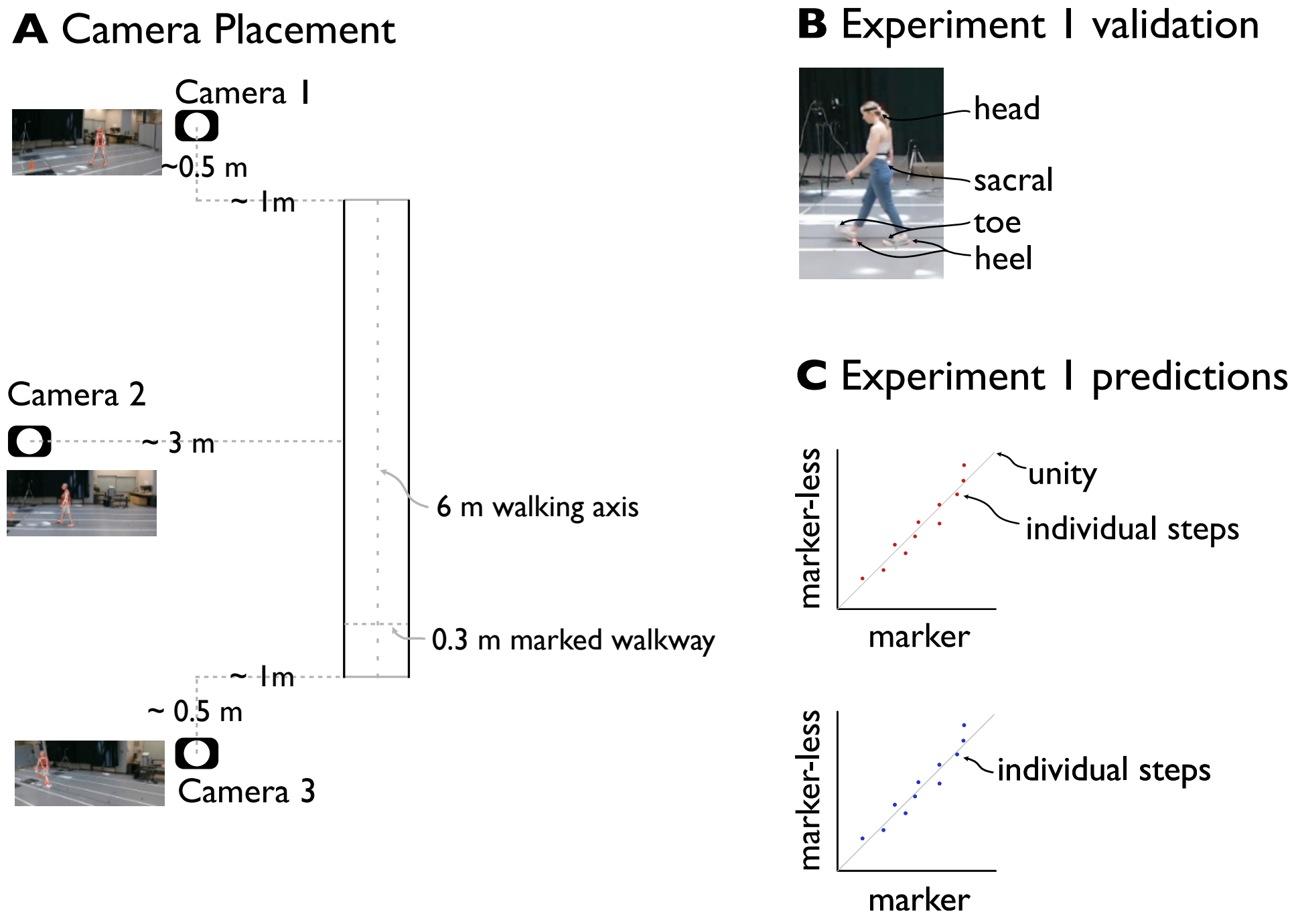
Townsend, M.A., 1985. Biped gait stabilization via foot placement. J. Biomech. 18, 21–38. https://doi.org/10.1016/0021-9290(85)90042-9

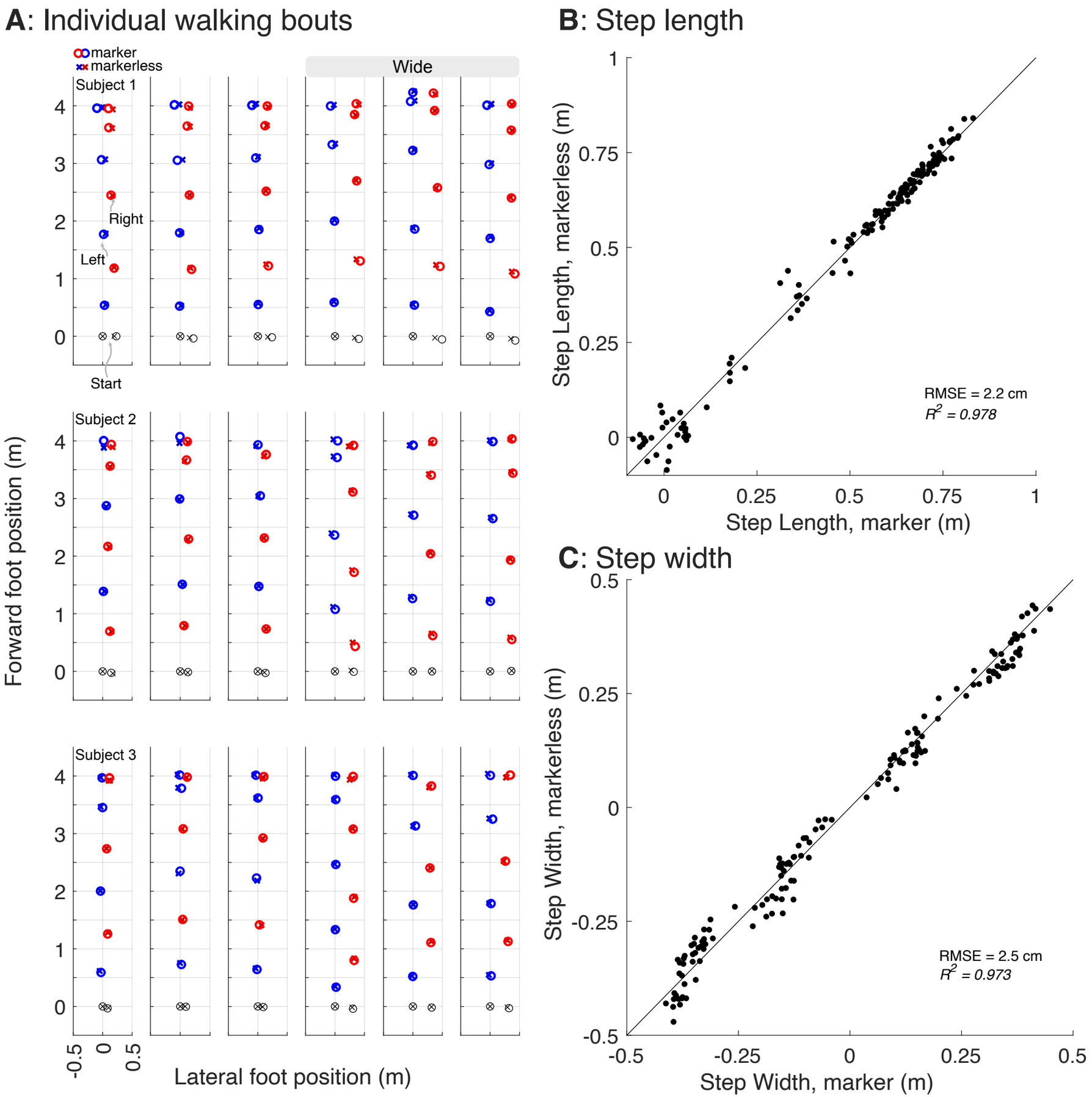
Viehweger, E., Pfund, L.Z., Hélix, M., Rohon, M.-A., Jacquemier, M., Scavarda, D., Jouve, J.-L., Bollini, G., Loundou, A., Simeoni, M.-C., 2010. Influence of clinical and gait analysis experience on reliability of observational gait analysis (Edinburgh Gait Score Reliability). Ann. Phys. Rehabil. Med. 53, 535–546. https://doi.org/10.1016/j.rehab.2010.09.002

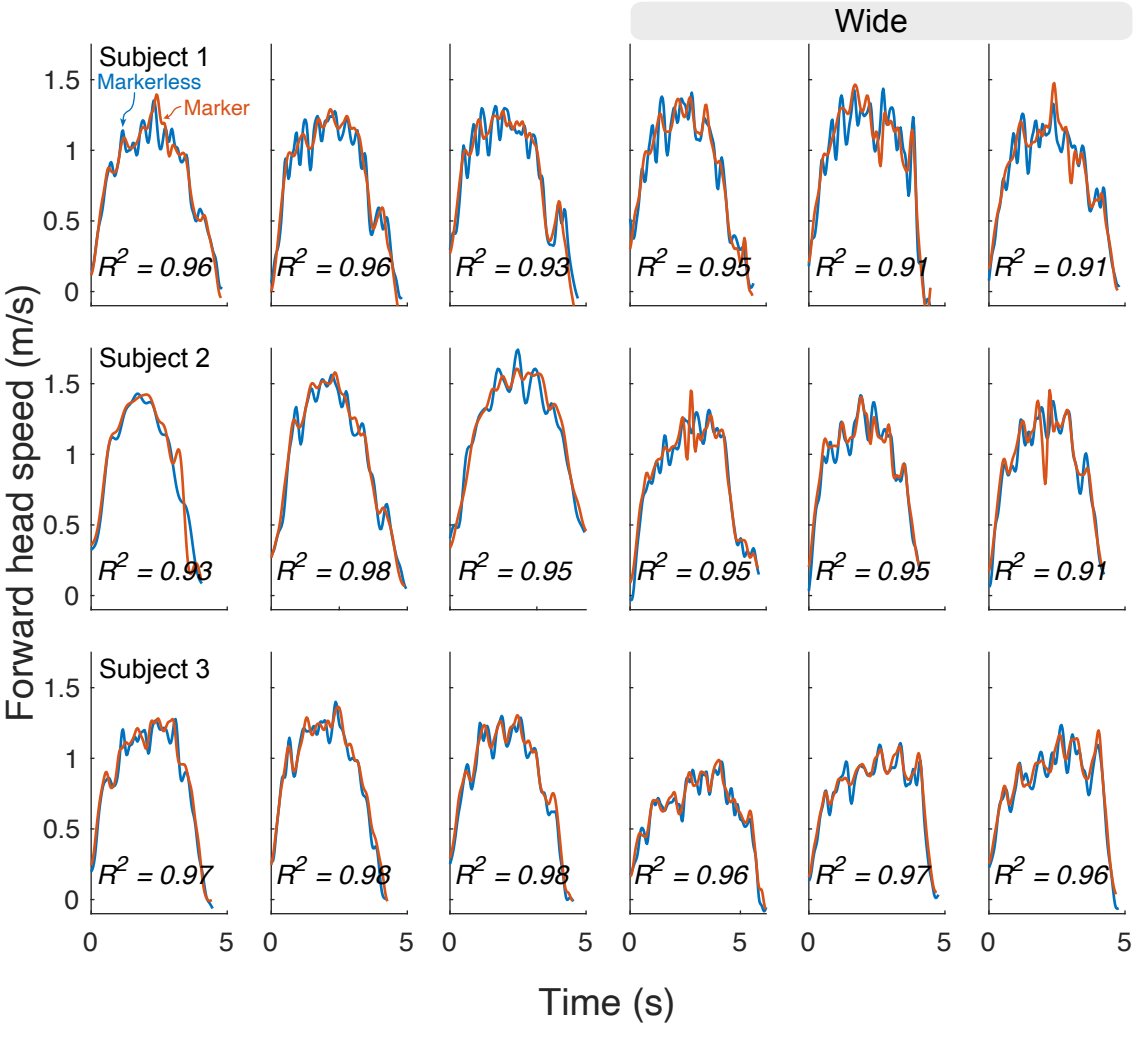
Walker, M.L., Austin, A.G., Banke, G.M., Foxx, S.R., Gaetano, L., Gardner, L.A., McElhiney, J., Morris, K., Penn, L., 2007. Reference group data for the functional gait assessment. Phys. Ther. 87, 1468–1477.

Wang, Y., Srinivasan, M., 2014. 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. https://doi.org/10.1098/rsbl.2014.0405

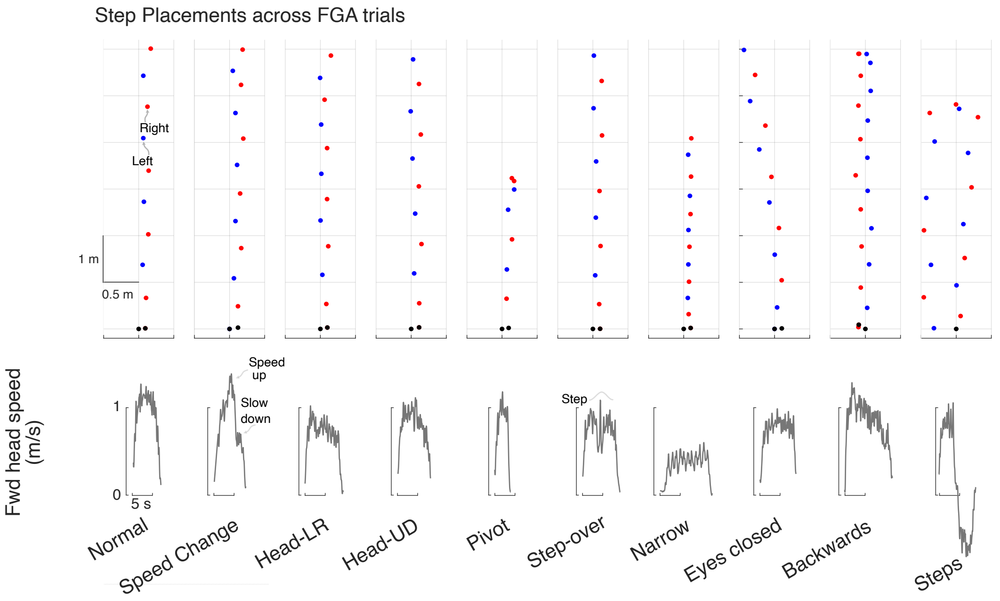
Wrisley, D.M., Kumar, N.A., 2010. Functional gait assessment: concurrent, discriminative, and predictive validity in community-dwelling older adults. Phys. Ther. 90, 761–773.


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

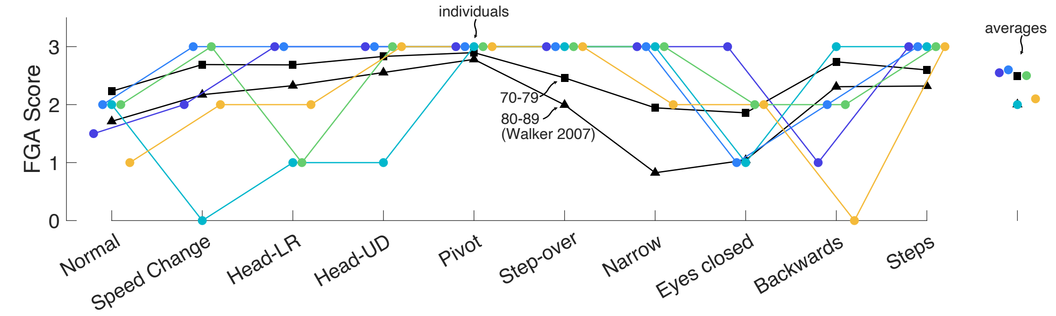

A: Individual walking bouts
marker
markerless
Wide
Subject 1
Subject 2
Subject 3
Right
Left
Start
Forward foot position (m)
Lateral foot position (m)
B: Step length
Step Length, markerless (m)
Step Length, marker (m)
RMSE = 2.2 cm
R2 = 0.978
C: Step width
Step Width, markerless (m)
Step Width, marker (m)
RMSE = 2.5 cm
R2 = 0.973

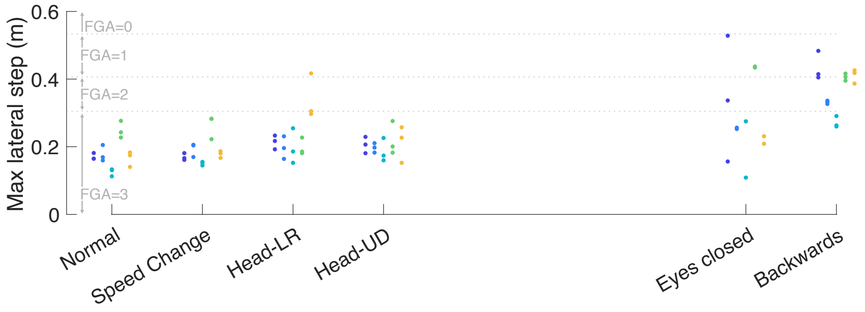
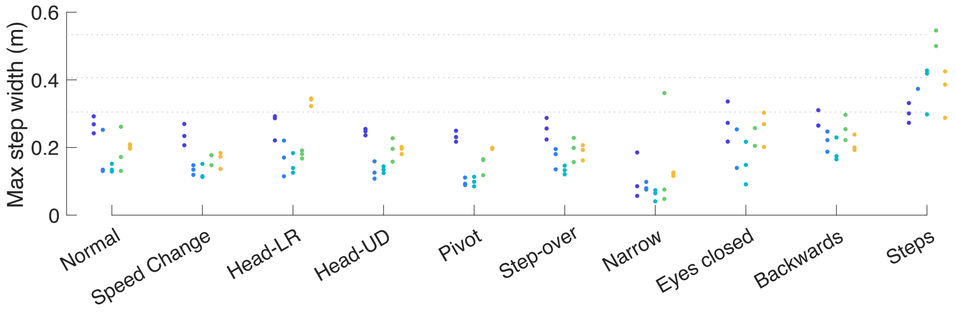
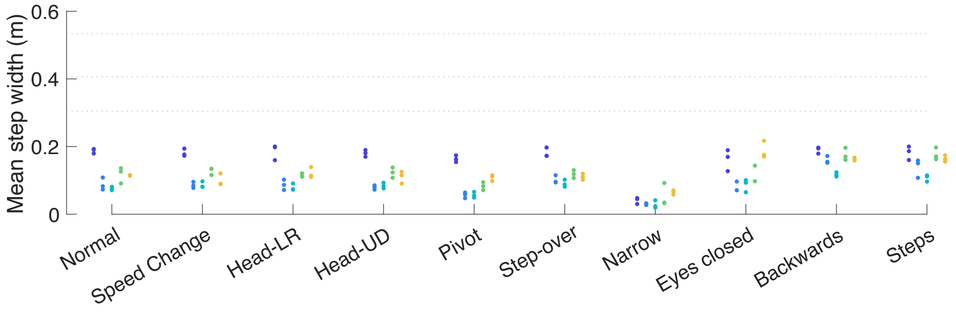
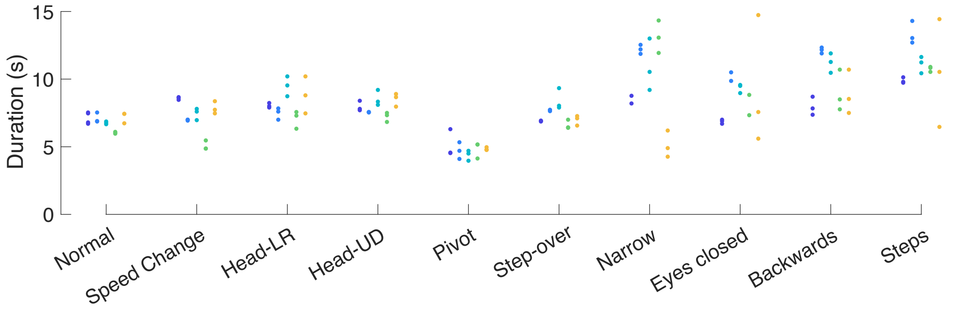

Wide
Subject 1
Markerless
Marker
Subject 2
Subject 3
R^2 = 0.96
R^2 = 0.96
R^2 = 0.93
R^2 = 0.95
R^2 = 0.91
R^2 = 0.91
R^2 = 0.93
R^2 = 0.98
R^2 = 0.95
R^2 = 0.95
R^2 = 0.95
R^2 = 0.91
R^2 = 0.97
R^2 = 0.98
R^2 = 0.98
R^2 = 0.96
R^2 = 0.97
R^2 = 0.96
Forward head speed (m/s)
Time (s)
0
0.5
1
1.5
5

A FGA: Subject data



B FGA: Scoring





C Proposed supplementary measurements