Nymeria-Gait: A Benchmark for Observer-Egocentric Real-World Gait Analysis

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Abstract. Spatiotemporal gait analysis is well established but remains underused in routine practice. We propose an observer-egocentric approach using smart glasses together with monocular 3D human and camera pose estimation to enable gait analysis during routine clinical observation. To support this, we introduce a benchmark dataset of egocentric video captured by a moving observer, with visual-inertial-based reference spatiotemporal parameters, and use it to evaluate a pipeline for real-world gait analysis. Results show the potential and current limitations of observer-egocentric gait analysis.

Keywords: Gait Analysis Benchmarking · Egocentric Dataset · 3D Human Pose Estimation

1 Introduction

Spatiotemporal gait analysis is a proven method for evaluating and studying human movement in clinical and research settings [43, 60]. However, most existing quantitative gait analysis approaches remain impractical for routine use, as they rely on laboratory setups, dedicated instrumentation, and trained personnel [25, 47, 50]. As a result, gait assessment remains largely confined to controlled environments [1], despite growing evidence that real-world measurements may better reflect everyday walking [3, 6, 18, 59]. These limitations highlight the need for gait analysis methods that are easy to use and operable in unconstrained, real-world environments.

Recent advances in computer vision, together with the emergence of smart glasses equipped with cameras and inertial sensors, offer new opportunities for practical gait analysis in real-world settings [14]. Monocular 3D human and camera pose estimation methods have improved substantially, enabling more accurate estimation in unconstrained environments [23, 35]. These developments suggest an observer-egocentric approach in which an external observer, such as a clinician or caregiver, records a walking subject using smart glasses during routine qualitative observation, without the need for complex setups or sensors on the subject

Despite its promise, this approach remains largely unexplored. The closest existing gait analysis approaches are limited to fixed-camera setups in controlled environments [10,27,36,51,57]. At the same time, most computer vision methods are evaluated almost exclusively using joint-level pose accuracy metrics, such as mean per-joint position error (MPJPE), which do not reflect biomechanically meaningful performance [35]. As a result, it remains unclear whether current methods are suitable for observer-egocentric gait analysis in real-world settings.

The goal of this work is to assess an observer-egocentric approach to spatiotemporal gait analysis. To this end, we introduce a benchmark, including a dataset captured from a moving observer using smart glasses with synchronized inertial reference, as well as a pipeline for spatiotemporal gait parameter extraction and evaluation.

2 Related Work

2.1 Gait Analysis Systems

Traditionally, gait analysis has relied on marker-based motion capture systems, which provide accurate measurements but require controlled environments, specialized equipment, and extensive setup [7, 11]. More recently, markerless approaches have been proposed to improve accessibility [24], including multi-camera systems [22, 41, 54], monocular methods from static or constrained viewpoints [10, 27, 36, 51, 57], and mobile smartphone-based methods, including gimbal-stabilized and handheld [9,42], which have shown promising agreement with reference measurements. However, these approaches remain limited to fixed or stabilized camera viewpoints and controlled environments. Other solutions such as pressure-sensitive walkways or wearable inertial sensors also require constrained capture areas, subject instrumentation, or careful calibration [45, 46]. Overall, existing gait analysis systems do not support simple and versatile spatiotemporal gait assessment in unconstrained, hands-free settings.

2.2 3D Pose Estimation

Monocular human motion reconstruction has substantially improved through the use of parametric body models such as SMPL [37], large-scale HMR-style frameworks with vision transformers [20,29], and methods that couple human motion with camera estimation in world coordinates [32, 58]. At the same time, there is growing interest in biomechanically accurate motion reconstruction [31, 33]. However, most existing approaches are still designed primarily for visual realism and are evaluated using joint-level pose accuracy metrics such as MPJPE. While these metrics are central for training and standardized comparison [39], they do not reflect task-level or biomechanically meaningful performance [35]. As a result, progress reported on existing benchmarks datasets such as Human3.6M [28], 3DPW [56], and EMDB [30] may not necessarily translate to reliable gait analysis.

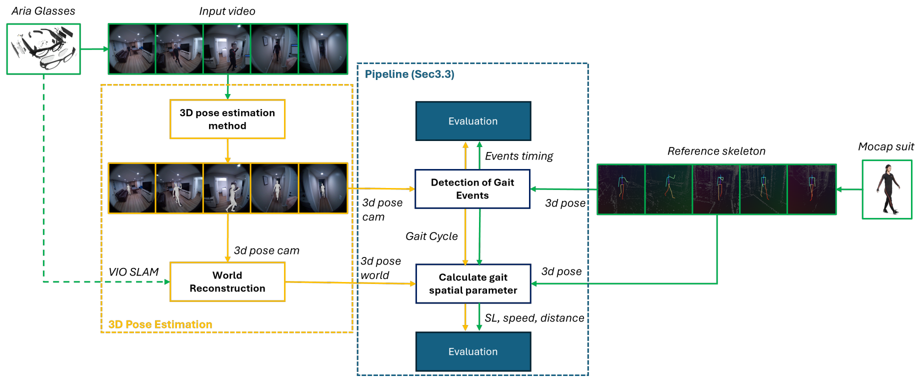

Fig. 1: Overview of our evaluation framework. Green represents Nymeria-Gait data, which includes egocentric observer videos, VIO SLAM, and reference skeleton data (Sec. 3.2). Orange represents the 3D pose estimation stage, which takes video input (optionally with VIO SLAM from the glasses) (Sec. 3.4) and returns 3D poses in both camera and world coordinates. Blue represents our gait estimation pipeline and evaluation (Sec. 3.3).

2.3 Datasets and Benchmarks

Existing datasets for gait and human motion analysis are primarily captured in controlled environments using fixed monocular or multi-camera setups [19, 34], which limits their suitability for observer-egocentric and mobile scenarios [53]. Several datasets provide gait measurements or walking sequences, but either lack synchronized video and rely on static viewpoints [8, 26], or do not include the precise reference information required for biomechanical analysis [8, 44, 52]. More recent real-world motion datasets introduce mobile cameras or egocentric viewpoints and enable the study of human motion from an observer's perspective [28, 30, 38, 56, 62]. However, these datasets are not designed for gait analysis, as they lack structured walking sequences, standardized gait annotations, or evaluation protocols based on spatiotemporal gait parameters (Details in Supplementary Table 1-S1). As a result, no existing dataset enables systematic benchmarking of observer-egocentric gait analysis in real-world settings.

3 Methods

3.1 Overview

Our goal is to evaluate observer-egocentric spatiotemporal gait analysis. To study this setting, we design a benchmark that combines egocentric smart-glasses recordings with synchronized inertial reference data and a modular pipeline for motion reconstruction and gait parameter extraction (Fig. 1). Monocular 3D human and camera pose estimation methods can be evaluated within this framework by comparing estimated gait parameters to reference measurements.

3.2 Nymeria-Gait Dataset

Nymeria-Gait is a dataset designed for observer-egocentric gait analysis which is a subset of the large all-purpose multimodal Nymeria dataset [38]. It consists of egocentric video recordings captured by mobile observers wearing smart glasses [14], while observing a participant equipped with an inertial motion capture suit (Xsens, NL). Video was recorded at 30 Hz and synchronized with reference motion captured at 240 Hz. All devices were time-synchronized, and recordings were spatially registered.

Nymeria-Gait contains 908 walking sequences from 54 subjects (26 males and 28 females; age: 18 to 50 years old, weight: 69±12 kg; height: 1.68±0.09 m), recorded across indoor and outdoor environments and spanning a total walking distance of approximately 7.9 km. The data include straight and turning motion, as well as flat and sloped terrain, captured during unconstrained real-world activities.

Detailed information on dataset construction, sequence selection, annotations, and statistics is provided in the supplementary material (Sec. S1).

3.3 Motion Reconstruction and Gait Evaluation

Pipeline: Given egocentric video captured by a moving observer, our framework reconstructs the subject's 3D motion and evaluates gait parameters derived from the reconstructed trajectories. Monocular 3D pose estimation methods are applied to the observer video for human motion relative to the camera. When required, reconstructed poses are expressed in a global coordinate system using the camera trajectory, enabling spatial gait analysis (Fig. 1).

Evaluation Protocol: The framework is designed to be modular, allowing different monocular pose estimation and camera localization methods to be interchanged and evaluated under a common protocol. Both camera-centric and world-centric reconstructions are supported, depending on the capabilities of the evaluated method.

Gait events are identified from foot trajectories relative to the pelvis along the walking direction for both the evaluated method and the synchronized reference, following prior work [49, 55, 61]. These events are then used to compute cycle, stance, swing, and double support durations. Stride length is also calculated on a cycle basis as the horizontal distance traveled by each foot between consecutive heel strikes. For each sequence, total displacement is computed from pelvis trajectory in the horizontal plane, and average walking speed is obtained by dividing this distance by sequence duration.

The resulting spatiotemporal parameters are compared between the evaluated method and the synchronized reference to assess performance. This design enables systematic benchmarking of observer-egocentric gait analysis pipelines by quantifying how reconstruction errors propagate to interpretable gait measures.

3.4 Method Selection for Experiments

We evaluated multiple monocular 3D human motion reconstruction methods and several variants of camera motion integration within the proposed framework. The evaluation considered both temporal and spatial gait parameters, allowing us to assess how different design choices affect gait estimation accuracy (details in Supplementary Sec. S2).

Based on this analysis, we selected the best-performing configuration for all subsequent experiments. In particular, we use WHAM [48] combined with camera trajectories provided by the smart-glasses visual-inertial (VIO) simultaneous localization and mapping (SLAM). This configuration achieved the most consistent performance across temporal gait events, spatial gait parameters, and trajectory accuracy in real-world conditions.

4 Experiments

4.1 Experimental Setup

Data Selection and Preprocessing: Experiments are conducted on our Nymeria-Gait dataset (Sec. 3.2) using our pipeline (Sec. 3.3). As Nymeria-Gait is a general-purpose dataset, some recordings revealed to be unsuitable, for example due to persistent foot occlusion that prevents reliable gait event detection. Such sequences were excluded.

The final evaluation set consists of 608 walking sequences, comprising 5,609 gait cycles and covering approximately 4.4 km of walking. These data were collected from 53 subjects across indoor and outdoor environments and correspond to 76 minutes of continuous walking.

Evaluation Metrics: To evaluate the proposed observer-based method, first, the event detection rate was calculated as the percentage of correctly identified heel-strike and toe-off events using the proposed method relative to the total number of these events identified by the reference. Then, based on the identified events, the errors (difference between the proposed and reference methods) were calculated for each cycle, stance, swing, and double support times. Similar error calculations were performed for stride length, gait speed and total distance.

The accuracy was defined as the mean of the individual errors and precision as their standard deviation (SD). In addition, the Pearson correlation coefficient (r) was used to assess the association between parameters obtained with the proposed and reference methods.

4.2 Quantitative Results

Temporal Parameters: The proposed observer-based method detected 96.6% of the 14,337 gait events, with a mean event timing error of 8.7 ms and SD of 37.3 ms. Detailed results for event detection and derived temporal parameters are reported in Table 1.

Parameter	Accuracy (ms)	Precision (ms)
Event Detection		
Heel strike	11.4	33.9
Toe-off	5.9	40.3
Gait Timing		
Cycle time	0.2	39.8
Stance time	-5.3	45.1
Swing time	5.5	43.5
Double support	-5.7	41.6

Table 1: Temporal gait parameter accuracy and precision across all analyzed gait cycles. Accuracy is reported as the mean error and precision as the standard deviation (SD).

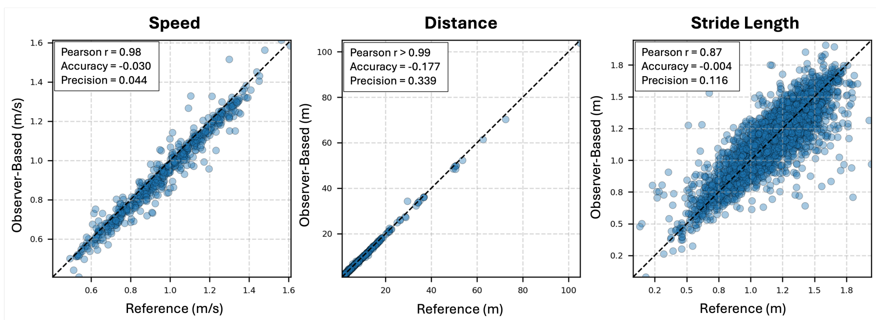

Fig. 2: Correlation between spatial gait parameters obtained using the proposed observer-based method and the reference method. Each point for speed and distance represents one of the 608 walking sequences, whereas each point for stride length represents one of the 5,609 gait cycles.

Overall, events were detected with frame-level accuracy, which propagated to accurate ($\leq 5.7ms$) and precise ($\leq 45.1ms$) temporal parameters. Importantly, 65.4% of detected gait events meet the recommended error tolerance threshold of 20.0 ms [12], indicating that the proposed approach is nearing recommended performance for gait assessment.

Spatial Parameters: Figure 2 reports the accuracy and precision of the estimated spatial gait parameters and illustrates their association with the reference. The mean errors for walking speed and total distance correspond to less than 4.7% of the average values observed in the dataset, while stride length shows a near-zero mean error and a precision corresponding to 9.8% of the average stride length.

For spatial parameters, acceptable performance thresholds are inherently application-dependent. Nevertheless, the proposed method shows strong association with the reference, with Pearson correlation coefficients >0.87 for walking speed, total distance, and stride length (Figure 2). The low errors for walking speed and total distance support their use in real-world settings. In contrast, a stride length precision close to 10% of the average value highlights a clear area for improvement. Still, these results indicate performance comparable to existing vision-based gait analysis approaches, despite operating in unconstrained, real-world settings with a moving observer [51, 57].

4.3 Discussion and Limitations

Overall, these results are encouraging given that they were obtained in an unconstrained, hands-free setting without subject instrumentation or calibration. The observed agreement with prior vision-based gait analysis studies suggests that the proposed approach may similarly meet minimal detectable change thresholds [16, 40]. A detailed analysis of how walking environment, terrain slope, observer viewpoint, and viewing distance influence measurement errors is provided in [5]. This analysis can expose limitations of current monocular motion reconstruction methods that are not captured by joint-level pose errors alone.

Several limitations should be noted. First, the smart glasses operate at 30 Hz, limiting temporal resolution. Second, the use of an inertial motion capture suit as reference limits the evaluation motivating future datasets specifically designed for biomechanical analysis. Third, our pipeline relies on SMPL but more recent body models [2, 15] may offer improved biomechanical fidelity. Evaluating them is a natural direction for future benchmarking on Nymeria-Gait. While only healthy participants were included, the underlying pose estimation and gait event detection methods have been validated on diverse populations, suggesting broader applicability [4, 13, 17, 21, 61]. Finally, although smart glasses were used here, the approach could generalize to any mobile device.

References

1. Benson, L.C., Räisänen, A.M., Clermont, C.A., Ferber, R.: Is this the real life, or is this just laboratory? a scoping review of imu-based running gait analysis. Sensors **22**(5), 1722 (2022)
2. Brégier, R., Fiche, G., Bravo-Sánchez, L., Lucas, T., Armando, M., Weinzaepfel, P., Rogez, G., Baradel, F.: Human mesh modeling for anny body. arXiv preprint arXiv:2511.03589 (2025)
3. Brognara, L., Arceri, A., Zironi, M., Traina, F., Faldini, C., Mazzotti, A.: Gait spatio-temporal parameters vary significantly between indoor, outdoor and different surfaces. Sensors **25**(5), 1314 (2025)
4. Bruening, D.A., Ridge, S.T.: Automated event detection algorithms in pathological gait. Gait & posture **39**(1), 472–477 (2014)
5. Cantaloube, A., Jolles, B.M., Favre, J.: Spatiotemporal gait analysis using video from a moving observer. Journal of Biomechanics p. 113402 (2026)
6. Carcreff, L., Gerber, C.N., Paraschiv-Ionescu, A., De Coulon, G., Newman, C.J., Aminian, K., Armand, S.: Comparison of gait characteristics between clinical and

daily life settings in children with cerebral palsy. Scientific reports **10**(1), 2091 (2020)
7. Chen, S., Lach, J., Lo, B., Yang, G.Z.: Toward pervasive gait analysis with wearable sensors: A systematic review. IEEE journal of biomedical and health informatics **20**(6), 1521–1537 (2016)
8. Chereshnev, R., Kertész-Farkas, A.: Hugadb: Human gait database for activity recognition from wearable inertial sensor networks. In: Analysis of Images, Social Networks and Texts: 6th International Conference, AIST 2017, Moscow, Russia, July 27–29, 2017, Revised Selected Papers 6. pp. 131–141. Springer (2018)
9. Cimorelli, A., Patel, A., Karakostas, T., Cotton, R.J.: Validation of portable in-clinic video-based gait analysis for prosthesis users. Scientific reports **14**(1), 3840 (2024)
10. Cotton, R.J., McClerklin, E., Cimorelli, A., Patel, A., Karakostas, T.: Transforming gait: video-based spatiotemporal gait analysis. In: 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). pp. 115–120. IEEE (2022)
11. Delp, S.L., Anderson, F.C., Arnold, A.S., Loan, P., Habib, A., John, C.T., Guendelman, E., Thelen, D.G.: Opensim: open-source software to create and analyze dynamic simulations of movement. IEEE transactions on biomedical engineering **54**(11), 1940–1950 (2007)
12. Dumphart, B., Slijepcevic, D., Unglaube, F., Kranzl, A., Baca, A., Horsak, B.: The effect of inaccurate initial contact events on kinematics in healthy and pathological gait. Gait & Posture p. 110012 (2025)
13. Eltoukhy, M., Kuenze, C., Andersen, M.S., Oh, J., Signorile, J.: Prediction of ground reaction forces for parkinson's disease patients using a kinect-driven musculoskeletal gait analysis model. Medical engineering & physics **50**, 75–82 (2017)
14. Engel, J., Somasundaram, K., Goesele, M., Sun, A., Gamino, A., Turner, A., Talattof, A., Yuan, A., Souti, B., Meredith, B., et al.: Project aria: A new tool for egocentric multi-modal ai research. arXiv preprint arXiv:2308.13561 (2023)
15. Ferguson, A., Osman, A.A.A., Bescos, B., Stoll, C., Twigg, C., Lassner, C., Otte, D., Vignola, E., Prada, F., Bogo, F., Santesteban, I., Romero, J., Zarate, J., Lee, J., Park, J., Yang, J., Doublestein, J., Venkateshan, K., Kitani, K., Kavan, L., Farra, M.D., Hu, M., Cioffi, M., Fabris, M., Ranieri, M., Modarres, M., Kadlecek, P., Khirodkar, R., Abdrashitov, R., Prévost, R., Rajbhandari, R., Mallet, R., Pearsall, R., Kao, S., Kumar, S., Parrish, S., Yu, S.I., Saito, S., Shiratori, T., Wang, T.L., Tung, T., Xu, Y., Dong, Y., Chen, Y., Xu, Y., Ye, Y., Jiang, Z.: Mhr: Momentum human rig (2025), `https://arxiv.org/abs/2511.15586`
16. Fernandes, R., Armada-da Silva, P., Pool-Goudaazward, A., Moniz-Pereira, V., Veloso, A.P.: Three dimensional multi-segmental trunk kinematics and kinetics during gait: Test-retest reliability and minimal detectable change. Gait & posture **46**, 18–25 (2016)
17. French, M.A., Koller, C., Arch, E.S.: Comparison of three kinematic gait event detection methods during overground and treadmill walking for individuals post stroke. Journal of Biomechanics **99**, 109481 (2020)
18. Galperin, I., Hillel, I., Del Din, S., Bekkers, E.M., Nieuwboer, A., Abbruzzese, G., Avanzino, L., Nieuwhof, F., Bloem, B.R., Rochester, L., et al.: Associations between daily-living physical activity and laboratory-based assessments of motor severity in patients with falls and parkinson's disease. Parkinsonism & related disorders **62**, 85–90 (2019)

19. Ghorbani, S., Mahdaviani, K., Thaler, A., Kording, K., Cook, D.J., Blohm, G., Troje, N.F.: Movi: A large multi-purpose human motion and video dataset. Plos one **16**(6), e0253157 (2021)
20. Goel, S., Pavlakos, G., Rajasegaran, J., Kanazawa, A., Malik, J.: Humans in 4d: Reconstructing and tracking humans with transformers. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 14783–14794 (2023)
21. Gonçalves, R.V., Fonseca, S.T., Araújo, P.A., Araújo, V.L., Barboza, T.M., Martins, G.A., Mancini, M.C.: Identification of gait events in children with spastic cerebral palsy: comparison between the force plate and algorithms. Brazilian Journal of Physical Therapy **24**(5), 392–398 (2020)
22. Gozlan, Y., Falisse, A., Uhlrich, S., Gatti, A., Black, M., Chaudhari, A.: Opencapbench: A benchmark to bridge pose estimation and biomechanics. arXiv preprint arXiv:2406.09788 (2024)
23. Guo, Y., Gao, T., Dong, A., Jiang, X., Zhu, Z., Wang, F.: A survey of the state of the art in monocular 3d human pose estimation: Methods, benchmarks, and challenges. Sensors (Basel, Switzerland) **25**(8), 2409 (2025)
24. Hellsten, T., Karlsson, J., Shamsuzzaman, M., Pulkkis, G.: The potential of computer vision-based marker-less human motion analysis for rehabilitation. Rehabilitation Process and Outcome **10**, 11795727211022330 (2021)
25. Hobani, S., Alhakami, A.M., Uddin, S., Ahmad, F., Alsobayel, H.: Perceived application and barriers for gait assessment in physical therapy practice in saudi arabia. Life **13**(1), 50 (2022)
26. Hofmann, M., Geiger, J., Bachmann, S., Schuller, B., Rigoll, G.: The tum gait from audio, image and depth (gaid) database: Multimodal recognition of subjects and traits. Journal of Visual Communication and Image Representation **25**(1), 195–206 (2014)
27. Horsak, B., Simonlehner, M., Quehenberger, V., Dumphart, B., Wegscheider, P., Kranzl, A., Slijepcevic, D.: Validity and reliability of monocular 3d markerless gait analysis in simulated pathological gait: A comparative study with opencap. Journal of Biomechanics p. 112986 (2025)
28. Ionescu, C., Papava, D., Olaru, V., Sminchisescu, C.: Human3. 6m: Large scale datasets and predictive methods for 3d human sensing in natural environments. IEEE transactions on pattern analysis and machine intelligence **36**(7), 1325–1339 (2013)
29. Kanazawa, A., Black, M.J., Jacobs, D.W., Malik, J.: End-to-end recovery of human shape and pose. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 7122–7131 (2018)
30. Kaufmann, M., Song, J., Guo, C., Shen, K., Jiang, T., Tang, C., Zárate, J.J., Hilliges, O.: Emdb: The electromagnetic database of global 3d human pose and shape in the wild. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 14632–14643 (2023)
31. Keller, M., Werling, K., Shin, S., Delp, S., Pujades, S., Liu, C.K., Black, M.J.: From skin to skeleton: Towards biomechanically accurate 3d digital humans. ACM Transactions on Graphics (TOG) **42**(6), 1–12 (2023)
32. Kocabas, M., Yuan, Y., Molchanov, P., Guo, Y., Black, M.J., Hilliges, O., Kautz, J., Iqbal, U.: Pace: Human and camera motion estimation from in-the-wild videos. In: 2024 International Conference on 3D Vision (3DV). pp. 397–408. IEEE (2024)
33. Koleini, F., Saleem, M.U., Wang, P., Xue, H., Helmy, A., Fenwick, A.: Biopose: Biomechanically-accurate 3d pose estimation from monocular videos. arXiv preprint arXiv:2501.07800 (2025)

34. Kwolek, B., Michalczuk, A., Krzeszowski, T., Switonski, A., Josinski, H., Wojciechowski, K.: Calibrated and synchronized multi-view video and motion capture dataset for evaluation of gait recognition. Multimedia Tools and Applications **78**(22), 32437–32465 (2019)
35. Liu, Y., Qiu, C., Zhang, Z.: Deep learning for 3d human pose estimation and mesh recovery: A survey. Neurocomputing p. 128049 (2024)
36. Lonini, L., Moon, Y., Embry, K., Cotton, R.J., McKenzie, K., Jenz, S., Jayaraman, A.: Video-based pose estimation for gait analysis in stroke survivors during clinical assessments: a proof-of-concept study. Digital Biomarkers **6**(1), 9–18 (2022)
37. Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., Black, M.J.: Smpl: A skinned multi-person linear model. In: Seminal Graphics Papers: Pushing the Boundaries, Volume 2, pp. 851–866 (2023)
38. Ma, L., Ye, Y., Hong, F., Guzov, V., Jiang, Y., Postyeni, R., Pesqueira, L., Gamino, A., Baiyya, V., Kim, H.J., et al.: Nymeria: A massive collection of multimodal egocentric daily motion in the wild. In: European Conference on Computer Vision. pp. 445–465. Springer (2024)
39. Martinez, J., Hossain, R., Romero, J., Little, J.J.: A simple yet effective baseline for 3d human pose estimation. In: Proceedings of the IEEE international conference on computer vision. pp. 2640–2649 (2017)
40. Meldrum, D., Shouldice, C., Conroy, R., Jones, K., Forward, M.: Test–retest reliability of three dimensional gait analysis: Including a novel approach to visualising agreement of gait cycle waveforms with bland and altman plots. Gait & posture **39**(1), 265–271 (2014)
41. Pagnon, D., Domalain, M., Reveret, L.: Pose2sim: an end-to-end workflow for 3d markerless sports kinematics—part 1: robustness. Sensors **21**(19), 6530 (2021)
42. Peiffer, J., Shah, K., Djuraskovic, I., Anarwala, S., Abdou, K., Patel, R., Jayabalan, P., Pennicooke, B., Cotton, R.J.: Portable biomechanics laboratory: Clinically accessible movement analysis from a handheld smartphone. arXiv preprint arXiv:2507.08268 (2025)
43. Perry, J., Burnfield, J.: Gait analysis: normal and pathological function. CRC Press (2024)
44. Ranjan, R., Ahmedt-Aristizabal, D., Armin, M.A., Kim, J.: Computer vision for clinical gait analysis: A gait abnormality video dataset. arXiv preprint arXiv:2407.04190 (2024)
45. Saboor, A., Kask, T., Kuusik, A., Alam, M.M., Le Moullec, Y., Niazi, I.K., Zoha, A., Ahmad, R.: Latest research trends in gait analysis using wearable sensors and machine learning: A systematic review. Ieee Access **8**, 167830–167864 (2020)
46. Sanders, O., Wang, B., Kontson, K.: Concurrent validity evidence for pressure-sensing walkways measuring spatiotemporal features of gait: A systematic review and meta-analysis. Sensors **24**(14), 4537 (2024)
47. Sharma, Y., Cheung, L., Patterson, K.K., Iaboni, A., et al.: Factors influencing the clinical adoption of quantitative gait analysis technologies for adult patient populations with a focus on clinical efficacy and clinician perspectives: protocol for a scoping review. JMIR research protocols **12**(1), e39767 (2023)
48. Shin, S., Kim, J., Halilaj, E., Black, M.J.: Wham: Reconstructing world-grounded humans with accurate 3d motion. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 2070–2080 (2024)
49. Sinitski, E.H., Lemaire, E.D., Baddour, N., Besemann, M., Dudek, N.L., Hebert, J.S.: Fixed and self-paced treadmill walking for able-bodied and transtibial amputees in a multi-terrain virtual environment. Gait & posture **41**(2), 568–573 (2015)

50. Stebbins, J., Harrington, M., Stewart, C.: Clinical gait analysis 1973–2023: Evaluating progress to guide the future. Journal of biomechanics **160**, 111827 (2023)
51. Stenum, J., Rossi, C., Roemmich, R.T.: Two-dimensional video-based analysis of human gait using pose estimation. PLoS computational biology **17**(4), e1008935 (2021)
52. Tian, Y., Wei, L., Lu, S., Huang, T.: Free-view gait recognition. PloS one **14**(4), e0214389 (2019)
53. Topham, L.K., Khan, W., Al-Jumeily, D., Hussain, A.: Human body pose estimation for gait identification: A comprehensive survey of datasets and models. ACM Computing Surveys **55**(6), 1–42 (2022)
54. Uhlrich, S.D., Falisse, A., Kidziński, Ł., Muccini, J., Ko, M., Chaudhari, A.S., Hicks, J.L., Delp, S.L.: Opencap: Human movement dynamics from smartphone videos. PLoS computational biology **19**(10), e1011462 (2023)
55. Ulrich, B., Santos, A.N., Jolles, B.M., Benninger, D.H., Favre, J.: Gait events during turning can be detected using kinematic features originally proposed for the analysis of straight-line walking. Journal of biomechanics **91**, 69–78 (2019)
56. Von Marcard, T., Henschel, R., Black, M.J., Rosenhahn, B., Pons-Moll, G.: Recovering accurate 3d human pose in the wild using imus and a moving camera. In: Proceedings of the European conference on computer vision (ECCV). pp. 601–617 (2018)
57. Wang, H., Su, B., Lu, L., Jung, S., Qing, L., Xie, Z., Xu, X.: Markerless gait analysis through a single camera and computer vision. Journal of Biomechanics **165**, 112027 (2024)
58. Wang, Y., Wang, Z., Liu, L., Daniilidis, K.: Tram: Global trajectory and motion of 3d humans from in-the-wild videos. In: European Conference on Computer Vision. pp. 467–487. Springer (2024)
59. Warmerdam, E., Hausdorff, J.M., Atrsaei, A., Zhou, Y., Mirelman, A., Aminian, K., Espay, A.J., Hansen, C., Evers, L.J., Keller, A., et al.: Long-term unsupervised mobility assessment in movement disorders. The Lancet Neurology **19**(5), 462–470 (2020)
60. Whittle, M.W.: Gait analysis: an introduction. Butterworth-Heinemann (2014)
61. Zeni Jr, J., Richards, J., Higginson, J.: Two simple methods for determining gait events during treadmill and overground walking using kinematic data. Gait & posture **27**(4), 710–714 (2008)
62. Zhang, S., Ma, Q., Zhang, Y., Qian, Z., Kwon, T., Pollefeys, M., Bogo, F., Tang, S.: Egobody: Human body shape and motion of interacting people from head-mounted devices. In: European conference on computer vision. pp. 180–200. Springer (2022)