

Validation of lower limb joint center localization and kinematics in markerless motion capture during sloped walking

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Title: Validation of lower limb joint center localization and kinematics in markerless motion capture during sloped walking

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22 **Abstract**

23 **Background**

24 Markerless motion capture (MLMC) enables natural motion analysis, yet its kinematic
25 validity during demanding tasks like steep sloped walking remains unclear. This study
26 compared lower limb joint centers and kinematics from MLMC and optical marker-based
27 motion capture (OMC) during multi-grade sloped walking.

28 **Methods**

29 Twenty-four healthy adults performed steady-state treadmill walking at level and sloped
30 conditions ($\pm 7.5\%$ and $\pm 15\%$), recorded synchronously using OMC (OptiTrack) and MLMC
31 (Theia3D). Participants wore form-fitting suits to minimize silhouette recognition errors.
32 Kinematic calculations were standardized using Visual3D. Validity was assessed via root
33 mean square error, Pearson correlations, Bland-Altman analysis, and 1D statistical parametric
34 mapping (SPM).

35 **Results**

36 3D lower limb joint center coordinates demonstrated extremely high agreement ($r > 0.999$)
37 across all slopes. While sagittal kinematics showed high waveform similarity, a constant
38 pelvic tilt offset emerged due to differing initial inclination definitions, alongside significant
39 deviations in ankle sagittal kinematics across most of the gait cycle.

40 **Conclusions**

41 Frontal and transverse plane kinematics exhibited joint-specific errors. Although high inter-
42 subject variability masked widespread significant SPM differences at the knee, wide limits of
43 agreement and significant deviations occurred in hip and ankle transverse planes.
44 Furthermore, downhill walking amplified hip frontal plane errors compared to level or uphill
45 conditions, presumably because strong eccentric contractions and shock absorption increased
46 OMC soft tissue artifacts. MLMC joint center tracking is highly robust during steep sloped

47 walking, supporting its application in complex field measurements. However, cautious data
48 interpretation is required regarding the initial pelvic offset and amplified hip and ankle
49 transverse and frontal plane errors under demanding tasks.

50

51 Keywords: Markerless motion capture; Joint center; Kinematics; Sloped walking; Deep
52 learning

53

Background

Over the past few decades, optical marker-based motion capture (OMC) has served as the gold standard for kinematic analysis in biomechanics research ^{1,2}. However, OMC has inherent challenges, such as soft tissue artifact (STA) ³⁻⁵ and variability in measurement accuracy due to human error in marker placement ^{6,7} has garnered attention as a method capable of non-invasively measuring natural movement kinematics by eliminating the need for equipment attached to the body ^{8,9}.

With the rise of MLMC, the process of defining joint centers (JCs) has transformed significantly. While conventional OMC estimates JCs from the outside in using regression equations or functional methods based on surface marker coordinates ^{10,11}, MLMC identifies JCs directly from image features or through model fitting based on large-scale anatomical datasets ^{12,13}. This fundamental difference in geometric approaches can be a factor causing systematic offsets in the kinematic data output between the two systems ¹², yet detailed investigations regarding their spatial agreement remain limited.

The validity of MLMC has previously been confirmed through validations involving a large number of subjects in steady-state movements such as level walking ¹⁴ and systematic reviews evaluating its practical utility in clinical settings ¹⁵. Furthermore, in tasks involving large joint ranges of motion and complex postural control, such as sloped walking, a decrease in estimation accuracy due to increased inter-segmental occlusion has traditionally been a challenge; however, recent studies have begun to report that MLMC demonstrates a certain level of reliability even under these environments ¹⁶. Nonetheless, these validations have been limited to gentle inclines simulating living spaces. Clarifying the degree of robustness possessed by the JC trajectories estimated by MLMC in response to demanding lower limb kinematics on steep slopes is an essential step for applying this technology to diverse field measurements ¹⁷.

The purpose of this study is to comparatively investigate the validity of three-dimensional lower limb joint center positions and subsequent joint angles calculated by MLMC and OMC during walking on level ground (0%) and multi-grade slopes (plus or minus 7.5% and 15%). This study quantifies the impact of environmental and kinematic changes caused by surface inclination on the spatial agreement between the two systems, and meticulously evaluates the influence of differences in calculation logic on kinematic outputs. Through this, we elucidate the measurement limits of markerless technology in demanding motor tasks, academically presenting its utility for future clinical and sports applications.

Methods

The subjects were 24 healthy adults with no history of orthopedic diseases in their lower limbs (10 males, 14 females, age 19.4 ± 1.3 years, height 165.6 ± 8.1 cm, body mass 59.5 ± 11.2 kg). Prior to the experiment, the purpose and procedures of the study were explained to the subjects, and written informed consent was obtained. This study was conducted with the approval of the Research Ethics Committee of Aomori University of Health and Welfare (Approval Number: 24078, approved on March 31, 2024). Clinical trial number: not applicable. The experimental task was steady-state walking on an instrumented treadmill at a speed of 4.0 km/h. Five slope conditions were set: level ground (0%), moderate slopes (7.5% uphill and 7.5% downhill), and steep slopes (15% uphill and 15% downhill), which were performed in a randomized order. Under each condition, following a 1-minute acclimatization walk, 2 minutes of walking data were recorded and targeted for analysis.

For the acquisition of kinematic data, optical marker-based motion capture (OMC) and markerless motion capture (MLMC) were used synchronously. During data acquisition, to minimize estimation errors caused by the looseness and swaying of clothing, the subjects

were asked to wear a form-fitting long-sleeved suit dedicated to motion capture on their upper body and compression tights on their lower body. In addition, they wore dedicated shoes with holes for marker placement. Although the wear and shoes were selected in sizes suitable for each subject, they were all unified to products from the same manufacturer. For the OMC, seven infrared cameras (OptiTrack Prime 13x, NaturalPoint, USA) were used, with the sampling frequency set to 150 Hz. Reflective markers were placed on the body surface of the subjects based on the Plug-in Gait model¹⁰. Furthermore, to improve the definition accuracy of the foot segment, a tracking marker was placed on the fifth metatarsal head. During static trials, additional markers were attached to the medial femoral condyle and the medial malleolus to define the knee and ankle joint centers. Simultaneously, for the MLMC, eight video cameras (Qualisys, Sweden) were placed between the OMC cameras (Figure 1), recording walking images at the same sampling frequency of 150 Hz. Both systems were calibrated in the same global coordinate system before the start of the experiment.

*** Figure 1 near here. ***

Regarding the processing of the acquired data, the OMC data were subjected to marker trajectory labeling and missing value interpolation using Motive software (NaturalPoint, USA), and then smoothed with a low-pass filter (cutoff frequency of 6 Hz). Subsequently, a lower limb link-segment model was constructed using Visual3D software (HAS-Motion, Canada), and the three-dimensional coordinates of each joint center (hip, knee, and ankle) and joint angles were calculated. Meanwhile, the MLMC video data were processed using Theia3D software (Theia Markerless, v2023.02.3, Canada) to extract the anatomical features of the subjects from the images and perform pose estimation¹⁸.

Thereafter, similar to the OMC, the data were imported into Visual3D software, a lower limb link-segment model was constructed, and the three-dimensional coordinates of each joint center and joint angles were calculated. Through the above processing, the segment definition and joint center estimation methods rely on algorithms specific to each system. Conversely, joint angles were calculated using Cardan angles in Visual3D, and by unifying the reference segment definitions and sign conventions, the outputs of both systems were compared under conditions with standardized calculation algorithms.

In the statistical analysis, steady-state gait cycles were extracted from the recorded 2-minute data. The identification of gait cycles was based on kinematic data, using heel strike as the reference event. The period from this event to the next ipsilateral identical event (i.e., a stride) was defined as one gait cycle, and each gait cycle was time-normalized to 100%. All gait cycles extracted from each subject were averaged after time normalization to calculate a representative waveform. Then, for the three-dimensional coordinates of each joint center obtained from OMC and MLMC, the coordinate differences in each axis (x, y, and z) directions were calculated, and the root mean square error (RMSE) for each was determined. The RMSE was also calculated for the joint angles in each plane. Additionally, Pearson correlation coefficients between the averaged OMC and MLMC waveforms, obtained by averaging the representative waveforms of each subject, were calculated to evaluate the similarity of the waveform shapes across one entire gait cycle. To evaluate systematic errors (additive and proportional errors) between the two systems, Bland-Altman analysis was used¹⁹. Furthermore, to evaluate the continuous agreement and significant differences of the time-series waveforms across one entire gait cycle, a one-dimensional paired t-test using Statistical Parametric Mapping (SPM) was conducted^{20,21}. At this time, to adjust for multiple comparisons across the three anatomical planes of each joint, the significance level was set to

alpha = 0.017 using the Bonferroni correction. All statistical processing was executed using R (R Foundation for Statistical Computing, Austria).

Results

Regarding the temporal parameters of gait across all conditions at a constant walking speed of 4.0 km/h, stride length ranged from 1.17 ± 0.06 m (15% downhill) to 1.26 ± 0.07 m (15% uphill), compared to 1.23 ± 0.05 m on level ground. Consequently, cadence was highest during the 15% downhill condition (113.21 ± 5.35 steps/min) and lowest during the 15% uphill condition (104.67 ± 6.34 steps/min), while the level walking cadence was 107.29 ± 4.39 steps/min. The proportion of the stance phase remained relatively consistent across all slopes, varying narrowly between $64.77 \pm 0.94\%$ (15% downhill) and $66.34 \pm 0.83\%$ (15% uphill). In this study, regarding the 3D coordinates of lower limb joint centers and joint angles calculated from OMC and MLMC, we verified time-series differences across the entire gait cycle using SPM, in addition to waveform evaluation using RMSE and Pearson correlation coefficients. The 3D coordinates of the hip (RHJC), knee (RKJC), and ankle (RAJC) joint centers demonstrated extremely high agreement between the systems (Supplementary Tables 1, 3-5). During level walking (0%) and all sloped conditions ($\pm 7.5\%$, $\pm 15\%$), Pearson correlation coefficients (r) for all axes ranged from 0.808 to 1.000, and RMSE remained at low values (3.6 to 16.4 mm) (Supplementary Table 1). These results confirmed that the geometric joint center identification process based on MLMC is robust against large kinematic changes in the lower extremities associated with surface inclination.

The results of the post-hoc tests using 1D SPM revealed that the system discrepancies in joint angles depended strongly on the anatomical plane (axis) being analyzed and the specific phase of the gait cycle (Figures 2-6). In sagittal plane motion (X-axis), the flexion

and extension angles of the knee and hip were in high agreement ($r = 0.994$ to 0.999) (Supplementary Table 2), and SPM showed no significant deviations over most of the gait cycle, except for a brief section (a few percent) during mid-stance (Figures 2-6). On the other hand, for anterior and posterior pelvic tilt (X-axis), significant systematic differences (additive errors of -2.7° to -3.9°) were observed over a wide range in all conditions (Table 1, Figures 2-6). Furthermore, for ankle dorsiflexion and plantarflexion (X-axis), significant differences with offsets were detected across the majority of the gait cycle (stance phase 0-57% and swing phase 63-100%), excluding the transition period from double limb support to the swing phase (Table 4, Figures 2-6).

In frontal (Y-axis) and transverse (Z-axis) plane motions, different error characteristics were observed for each joint (Tables 2, 3, Supplementary Table 2). For the Y and Z axes of the knee joint, no significant clusters on SPM were detected, except for a localized section from the late swing phase to initial contact (Table 3, Figures 2-6). Conversely, for the Z axis of the hip and ankle joints, significant system differences were detected over a wide range centered around mid-stance (approximately 28-69%) in all conditions (Tables 2, 4, Figures 2-6). Furthermore, in the Y axis of the hip joint, significant differences that were limited during level and uphill conditions specifically expanded over a wide range from the stance phase to the swing phase only under downhill conditions (-7.5% , -15%) (Table 2, Figures 4, 6).

*** Table 1-4 and Figure 2-6 near here. ***

Discussion

This study comparatively investigated the validity of lower limb joint kinematics calculated from MLMC and OMC during walking on level ground and multi-grade slopes. As a result, while 3D coordinate estimation of joint centers demonstrated extremely high agreement across all conditions (Supplementary Tables 1, 3-5), SPM revealed systematic offsets in the sagittal plane caused by anterior-posterior pelvic tilt (Table 1, Figures 2-6), widespread discrepancies in the transverse plane (Z-axis) at the hip and ankle joints (Tables 2, 4, Figures 2-6), and amplified errors in the hip frontal plane (Y-axis) specific to downhill slopes (Table 2, Figures 4, 6). The high spatial agreement of joint centers between the two systems indicates that the deep learning algorithms implemented in MLMC function robustly even in tasks prone to occlusion, such as steep slopes¹⁶. Whereas OMC cannot avoid the influence of STA during the process of estimating JCs from surface markers using regression equations⁴, the MLMC approach is considered to enable stable joint center tracking that is less dependent on environmental changes¹².

On the other hand, the significant discrepancies observed in joint angles using SPM are highly likely attributable to fundamental differences in local coordinate system definitions between the two systems and the inference and correction mechanisms inherent in the MLMC deep learning model. Particularly, it is important that a significant offset occurred in anterior-posterior pelvic tilt (X-axis) during the stance phase and initial contact (Table 1, Figures 2-6). While OMC constructs the pelvic coordinate system from surface markers, MLMC estimates pelvic posture from image features, which tends to cause a constant difference in the estimation of initial pelvic inclination¹⁴. Recently, D'Souza et al.²² also reported a systematic offset in which Theia3D underestimates anterior pelvic tilt compared to marker-based systems in gait analysis of healthy individuals and patients, and the results of this study strongly align with this finding²². As indicated by the SPM results, it is inferred that this difference in pelvic estimation propagated to hip sagittal kinematics, becoming the

primary factor generating a constant RMSE despite the waveforms showing high correlation^{3,6}.

Furthermore, the widespread significant differences observed primarily during mid-stance in the transverse plane (Z-axis) of the hip and ankle joints highlight the limitations of the approach in estimating posture around the longitudinal axis and its deviation from true bone kinematics (Tables 2, 4, Figures 2-6). Tracking markers in OMC are strongly affected by STA, causing different errors in apparent joint motion depending on the body part and movement⁵. For example, in the hip joint, which has thick soft tissue, it has been revealed that STA introduces more complex errors relative to true bone kinematics. A study by Fiorentino et al.²³ demonstrated that while marker measurements cause an average overestimation of 5.8 degrees toward internal rotation relative to true hip kinematics, they can underestimate the range of motion (ROM) across the entire movement by up to 21.8 degrees²³. Moreover, in their 2020 study, they emphasized that this underestimation caused by STA is a major error factor that propagates to rigid-body model outputs²⁴. In this study, the detection of large RMSE and significant SPM differences between MLMC and OMC in the Z-axis of the hip and other joints is considered to strongly reflect exactly these OMC-specific measurement errors (complex artifacts such as underestimation) and the different characteristics of the MLMC inference algorithm. MLMC tends to output posture by inferring and correcting toward average, smooth kinematics accumulated in training datasets, rather than relying solely on image features. Consequently, it is speculated that a systematic discrepancy arose between the OMC waveforms, which fluctuate complexly due to inherent STA, and the MLMC waveforms, which are smoothed based on training data, leading to substantial errors. Notably, the fact that widespread significant clusters were not detected in the Y and Z axes of the knee joint, despite observed decreases in RMSE and correlation coefficients, is thought to be because severe inter-subject STA noise (large standard

deviations) in the thigh and shank markers masked the detection of statistical significance (Table 3, Supplementary Table 2).

Additionally, it is noteworthy that these joint angle discrepancies characteristically increased in the hip frontal plane (Y-axis) and ankle sagittal plane (X-axis) during downhill slopes (Tables 2, 4, Figures 4, 6). Compared to level walking, downhill walking requires extremely strong eccentric contractions by lower limb muscle groups, such as the gluteus maximus and quadriceps, to control rapid center of mass descent and absorb shock, and postural control also tends to become asymmetrical^{25,26}. The bulging of soft tissues around the hip joint associated with such intense muscle activity, along with vibrations from landing impact, further amplifies STA on the OMC side during phases specific to downhill walking. In addition, when atypical kinematics such as complex foot clearance are required, MLMC attempts to correct toward overly smooth kinematics based on its training model. This highly likely caused the discrepancies between the two systems to become prominent only in environments subjected to extreme mechanical loads (downhill slopes).

There are several limitations in interpreting the findings of this study. First, the OMC kinematics used as the reference standard are not the absolute ground truth, as they inherently contain STA associated with skin marker movement. Although this study inferred that increased STA during downhill walking is one of the primary causes of expanded errors between the two systems, it is difficult to completely isolate the sources of inter-system errors without direct validation using true bone kinematics, such as biplanar videofluoroscopy. Second is the version dependency of the MLMC software (Theia3D). The pose estimation accuracy of MLMC changes continuously with updates to the training datasets and algorithms of its built-in deep learning networks. The robustness of estimation and the constant offsets associated with pelvic definitions obtained in this study strongly reflect the

characteristics of the specific software version used in this experiment, and future updates may improve or alter these error characteristics. Third is the control over the subjects physical characteristics and the experimental environment. This study included healthy adults with no lower limb orthopedic conditions and was conducted with participants wearing dedicated form-fitting suits to minimize MLMC silhouette recognition errors caused by loose clothing. Therefore, the results of this study merely demonstrate the accuracy under ideal environmental conditions for MLMC. Whether equivalent robustness is guaranteed for pathological gait with walking aids or while wearing loose-fitting clothing in actual clinical or sports settings requires future verification. Finally, the experimental task was limited to steady-state walking (4.0 km/h) on an instrumented treadmill. In actual outdoor sloped walking, continuous adjustments of step length and walking speed in response to changes in surface conditions and inclination angles, as well as more complex and asymmetrical postural control, are required. To verify the applicability of MLMC in more practical field environments, further data accumulation through methods such as overground measurements is necessary.

Conclusions

In conclusion, the proven high joint center tracking capability and high waveform reproducibility of sagittal plane kinematics strongly support that MLMC is sufficiently applicable for complex field measurements, such as on steep slopes¹⁷. However, continuous careful judgment is required when interpreting the initial pelvic offset and the rotational components in the frontal and transverse planes that increase under demanding tasks^{15,22}.

295 **Declarations**

296 Ethics approval and consent to participate

297 The study was conducted in accordance with the Declaration of Helsinki and approved by the
298 Research Ethics Committee of Aomori University of Health and Welfare (Approval Number:
299 24078, approved on March 31, 2024). Written informed consent was obtained from all
300 participants involved in the study.

301

302 Consent for publication

303 Not applicable.

304

305 Availability of data and materials

306 The datasets used and/or analysed during the current study are available from the
307 corresponding author on reasonable request.

308

309 Competing interests

310 The authors declare that they have no competing interests.

311

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Author contributions

HS: Conceptualization, Methodology, Investigation, Project administration, Writing - original draft, Writing - review & editing. TH: Formal analysis, Data curation, Software. YU: Visualization, Validation, Writing - review & editing. DK: Visualization, Validation, Writing - review & editing. TM: Supervision, Validation, Visualization, Writing - review & editing.

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Figure Legends

Figure 1. Experimental setup and camera layout.

Schematic representation of the experimental environment showing the participant walking on the instrumented treadmill. The layout illustrates the placement of the optical marker-based cameras (OMC) and the markerless video cameras (MLMC) surrounding the capture volume.

Figure 2. Statistical parametric mapping (SPM) results for lower limb joint kinematics during level walking.

The solid red line represents the markerless (MLMC) system data, while the solid black line indicates the marker-based (OMC) system data (horizontal axis: gait cycle [%]; vertical axis: angle [°]). The black bars at the top of the graph indicate periods of the gait cycle with statistically significant differences between the two systems, based on the SPM[t] statistic.

Figure 3. Statistical parametric mapping (SPM) results for lower limb joint kinematics during 7.5% uphill walking.

See Figure 2 for detailed descriptions of the statistical curves and shaded areas.

Figure 4. Statistical parametric mapping (SPM) results for lower limb joint kinematics during 7.5% downhill walking.

See Figure 2 for detailed descriptions of the statistical curves and shaded areas.

414 Figure 5. Statistical parametric mapping (SPM) results for lower limb joint kinematics during
415 15% uphill walking.

416 See Figure 2 for detailed descriptions of the statistical curves and shaded areas.

417

418 Figure 6. Statistical parametric mapping (SPM) results for lower limb joint kinematics during
419 15% downhill walking.

420 See Figure 2 for detailed descriptions of the statistical curves and shaded areas.

421

422 **Supplementary material**

423 Supplementary Table 1. Root mean square error (RMSE), mean absolute error (MAE), and
424 Pearson correlation coefficients (r) for three-dimensional lower limb joint centers.

425 Values indicate the positional errors and spatial agreement between the markerless and
426 marker-based motion capture systems across all walking conditions (level, $\pm 7.5\%$, and
427 $\pm 15\%$). RMSE and MAE values are presented in meters (m).

428

429 Supplementary Table 2. Root mean square error (RMSE), mean absolute error (MAE), and
430 Pearson correlation coefficients (r) for lower limb joint angles.

431 Values indicate the kinematic errors and waveform similarity between the markerless and
432 marker-based systems across all walking conditions. RMSE and MAE values are presented in
433 degrees ($^{\circ}$).

434

435 Supplementary Table 3. Bland-Altman analysis results for the hip joint center.

436 Values indicate the additive and proportional errors between the markerless and marker-
437 based systems across all walking conditions. Additive error is presented as the mean
438 difference with 95% lower and upper limits of agreement (LOA) in meters (m), along with
439 the corresponding p-value. Proportional error is evaluated using the Pearson correlation
440 coefficient (r) and its p-value.

441

442 Supplementary Table 4. Bland-Altman analysis results for the knee joint center.

443 Values indicate the additive and proportional errors between the markerless and marker-
444 based systems across all walking conditions. Additive error is presented as the mean
445 difference with 95% lower and upper limits of agreement (LOA) in meters (m), along with
446 the corresponding p-value. Proportional error is evaluated using the Pearson correlation
447 coefficient (r) and its p-value.

448

449 Supplementary Table 5. Bland-Altman analysis results for the ankle joint center.

450 Values indicate the additive and proportional errors between the markerless and marker-
451 based systems across all walking conditions. Additive error is presented as the mean
452 difference with 95% lower and upper limits of agreement (LOA) in meters (m), along with
453 the corresponding p-value. Proportional error is evaluated using the Pearson correlation
454 coefficient (r) and its p-value.

455

456 Tables

457 Table 1. Bland-Altman analysis results for pelvic angles.

Joint Angle	Plane	Conditions	Bias	SD	Lower LOA	Upper LOA	R ²	Slope
Pelvis angle	Sagittal	0%	-3.775	4.607	-12.805	5.256	0.729	-1.304
		7.5%Up	-3.900	4.693	-13.097	5.298	0.654	-1.400
		7.5%Down	-3.271	4.664	-12.412	5.869	0.793	-1.254
		15%Up	-3.872	4.747	-13.176	5.432	0.504	-1.379
		15%Down	-2.745	4.824	-12.199	6.710	0.763	-1.123
	Frontal	0%	-0.656	1.574	-3.741	2.429	0.801	-1.364
		7.5%Up	-0.668	1.615	-3.833	2.498	0.854	-1.428
		7.5%Down	0.566	1.646	-2.661	3.793	0.806	-1.369
		15%Up	-0.534	1.760	-3.983	2.915	0.728	-1.455
		15%Down	0.593	1.699	-2.737	3.923	0.832	-1.523
	Horizontal	0%	1.704	2.081	-2.375	5.784	0.262	-0.680
		7.5%Up	1.778	2.232	-2.597	6.154	0.068	-0.322
		7.5%Down	2.233	2.801	-3.257	7.724	0.259	-0.850
		15%Up	2.245	2.423	-2.504	6.994	0.302	-0.749
		15%Down	3.200	2.828	-2.343	8.744	0.269	-0.681

458 Values indicate the additive and proportional errors between the markerless and marker-
459 based systems across all walking conditions. Additive error is presented as the mean
460 difference with 95% lower and upper limits of agreement (LOA) in degrees (°), along with
461 the corresponding p-value. Proportional error is evaluated using the Pearson correlation
462 coefficient (r) and its p-value.

463

464 Table 2. Bland-Altman analysis results for hip joint angles.

Joint Angle	Plane	Conditions	Bias	SD	Lower LOA	Upper LOA	R ²	Slope
Hip angle	Saggital	0%	-3.077	5.565	-13.984	7.830	0.643	-1.205
		7.5%Up	-3.336	5.615	-14.341	7.669	0.476	-1.115
		7.5%Down	-1.941	5.576	-12.871	8.988	0.591	-1.332
		15%Up	-3.201	5.634	-14.244	7.841	0.303	-0.881
		15%Down	-0.901	5.825	-12.319	10.516	0.495	-1.368
	Frontal	0%	-1.299	1.890	-5.003	2.405	0.306	-0.532
		7.5%Up	-1.427	1.961	-5.270	2.417	0.230	-0.460
		7.5%Down	-1.886	2.160	-6.119	2.348	0.423	-0.802
		15%Up	-1.875	2.183	-6.154	2.404	0.466	-0.880
		15%Down	-1.334	2.339	-5.917	3.250	0.357	-0.759
	Horizontal	0%	2.164	6.469	-10.515	14.842	0.798	-1.886
		7.5%Up	2.756	6.282	-9.557	15.069	0.848	-1.764
		7.5%Down	2.731	6.549	-10.106	15.567	0.820	-1.789
		15%Up	2.069	6.786	-11.231	15.369	0.841	-1.853
		15%Down	1.629	6.537	-11.184	14.441	0.880	-1.777

465 The error metrics and statistical evaluations are identical to those described in Table 1.

466

467

468 Table 3. Bland-Altman analysis results for knee joint angles.

Joint Angle	Plane	Conditions	Bias	SD	Lower LOA	Upper LOA	R ²	Slope
Knee angle	Saggital	0%	0.449	2.223	-3.908	4.805	0.447	-0.698
		7.5%Up	0.259	2.104	-3.866	4.383	0.163	-0.255
		7.5%Down	1.197	2.314	-3.339	5.732	0.089	-0.339
		15%Up	0.236	2.231	-4.138	4.609	0.030	-0.084
		15%Down	1.737	2.281	-2.733	6.208	0.001	-0.021
	Frontal	0%	1.050	2.771	-4.381	6.482	0.515	-0.778
		7.5%Up	0.818	2.900	-4.866	6.503	0.516	-0.825
		7.5%Down	-0.447	3.722	-7.742	6.847	0.547	-1.031
		15%Up	0.445	3.591	-6.593	7.484	0.441	-0.907
		15%Down	-0.654	3.985	-8.465	7.157	0.571	-1.113
	Horizontal	0%	-3.787	8.193	-19.846	12.272	0.728	-1.299
		7.5%Up	-4.292	8.277	-20.515	11.930	0.803	-1.376
		7.5%Down	-4.574	8.798	-21.818	12.669	0.879	-1.557
		15%Up	-3.779	8.675	-20.781	13.224	0.852	-1.369
		15%Down	-3.670	8.735	-20.791	13.450	0.896	-1.529

469 The error metrics and statistical evaluations are identical to those described in Table 1.

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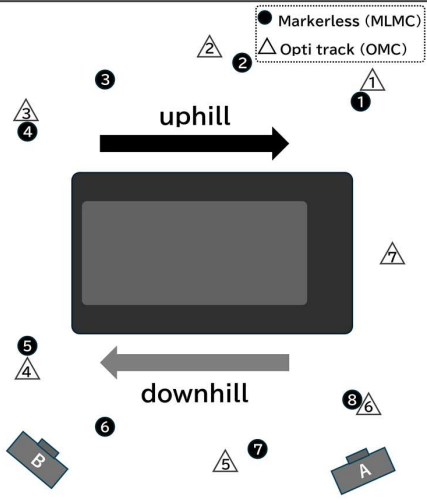
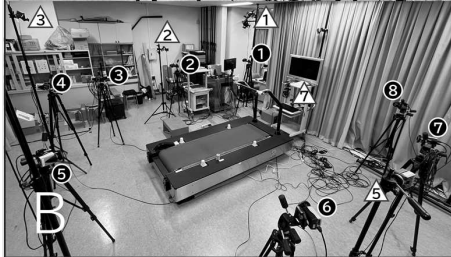
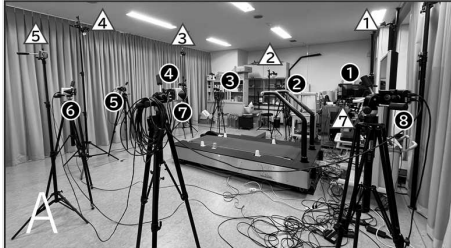
472 Table 4. Bland-Altman analysis results for ankle joint angles.

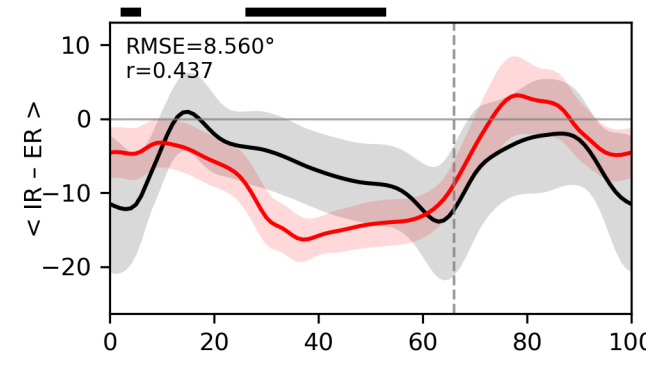
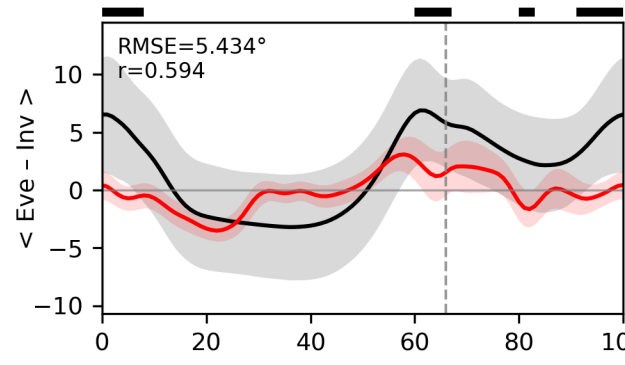
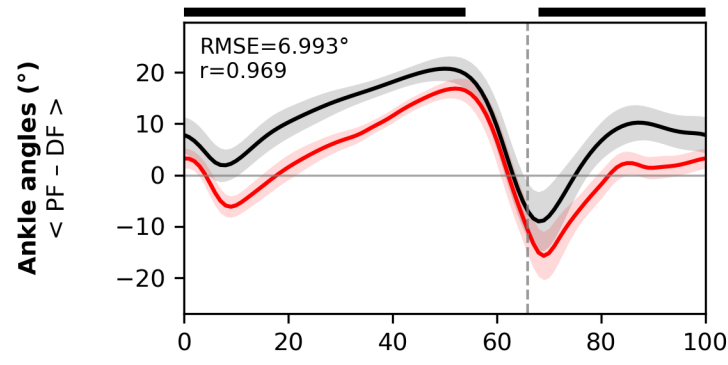
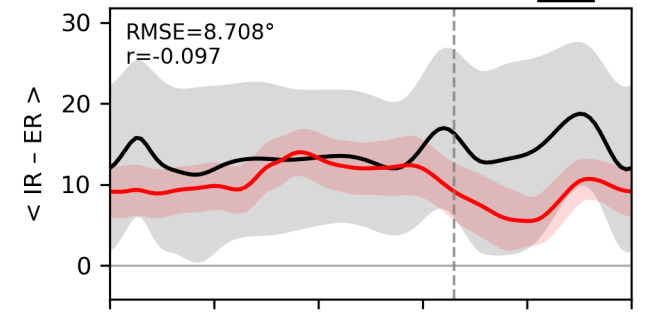
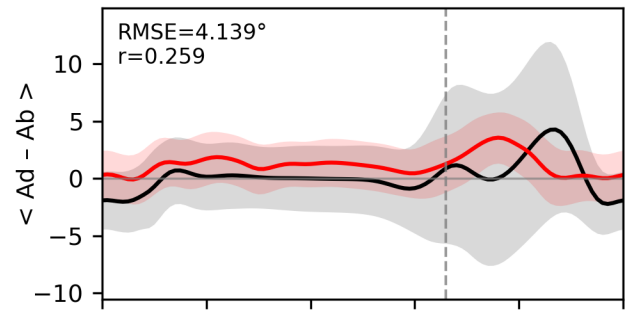
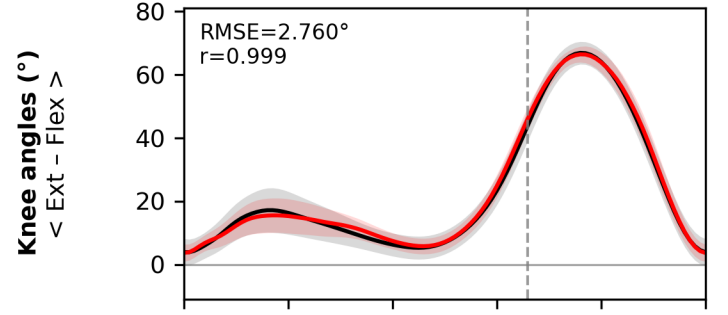
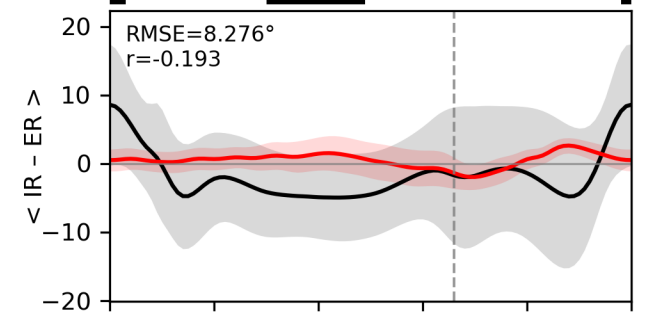
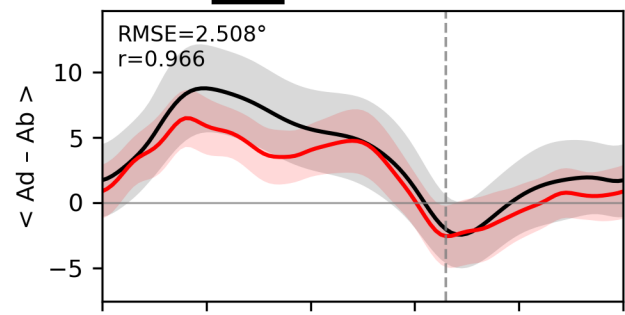
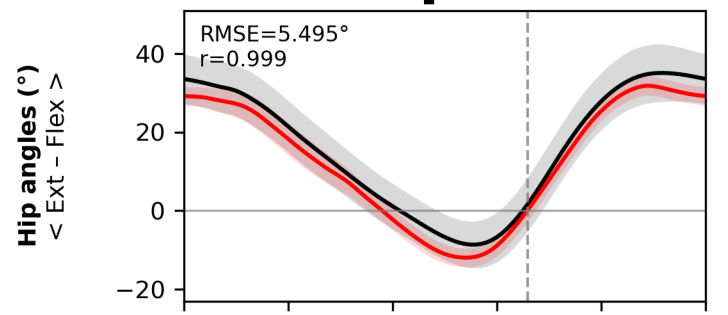
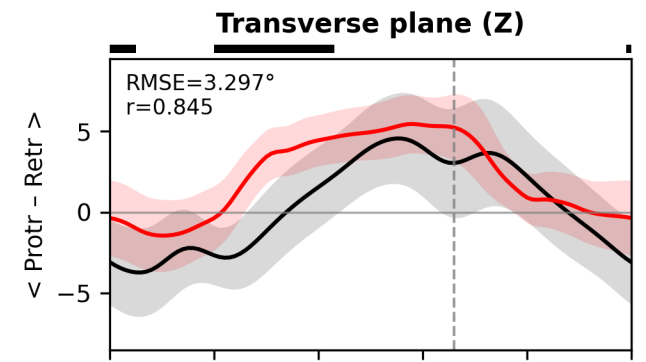
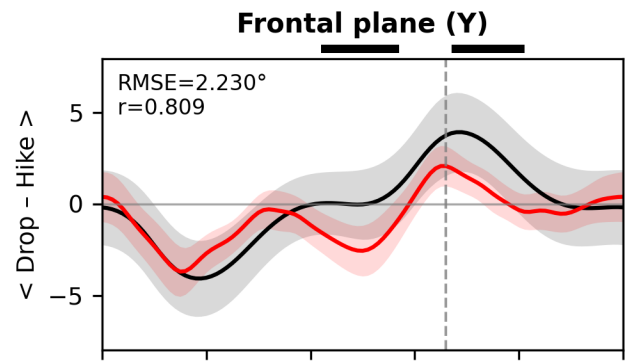
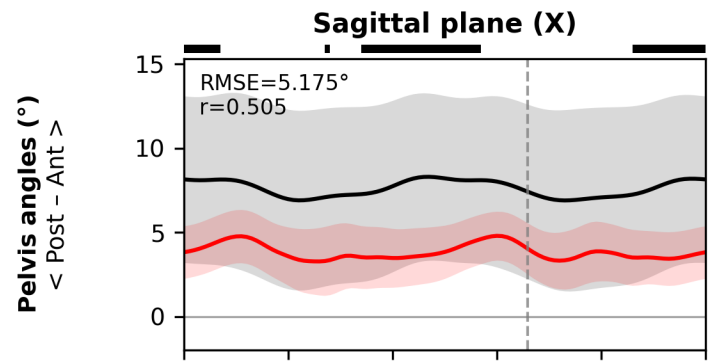
Joint Angle	Plane	Conditions	Bias	SD	Lower LOA	Upper LOA	R ²	Slope
Ankle angle	Saggital	0%	-6.526	1.553	-9.571	-3.482	0.298	-0.450
		7.5%Up	-6.474	1.557	-9.527	-3.422	0.310	-0.333
		7.5%Down	-6.121	2.010	-10.061	-2.181	0.459	-0.759
		15%Up	-6.166	2.016	-10.117	-2.215	0.227	-0.308
		15%Down	-6.133	1.984	-10.022	-2.243	0.407	-0.606
	Frontal	0%	-1.863	4.123	-9.943	6.217	0.823	-1.873
		7.5%Up	-1.694	4.141	-9.811	6.423	0.873	-1.989
		7.5%Down	-1.161	4.022	-9.044	6.721	0.755	-1.421
		15%Up	-1.491	4.561	-10.430	7.448	0.795	-1.747
		15%Down	-1.079	4.215	-9.341	7.183	0.804	-1.497
	Horizontal	0%	-0.757	5.310	-11.165	9.652	0.201	-0.935
		7.5%Up	-0.850	5.710	-12.042	10.342	0.359	-1.151
		7.5%Down	-0.991	6.529	-13.788	11.806	0.362	-1.248
		15%Up	-0.961	6.718	-14.128	12.206	0.299	-1.104
		15%Down	-1.655	6.697	-14.781	11.471	0.321	-1.148

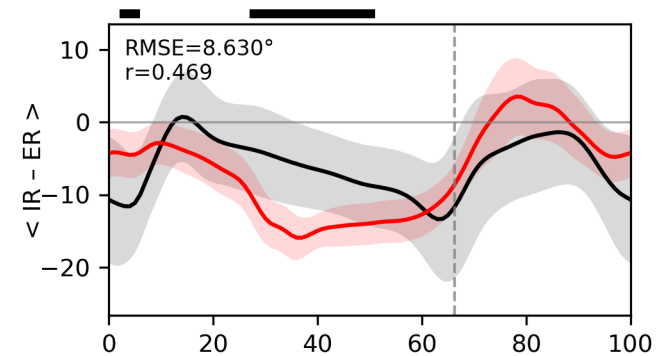
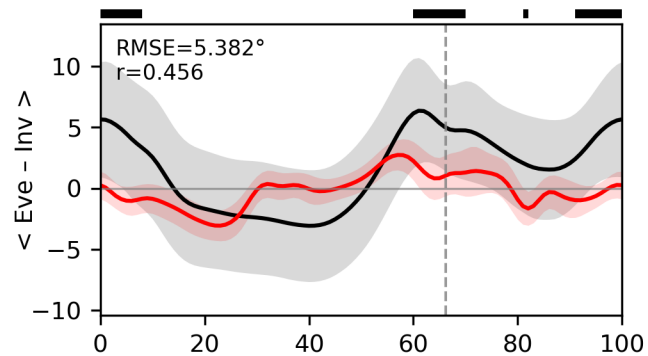
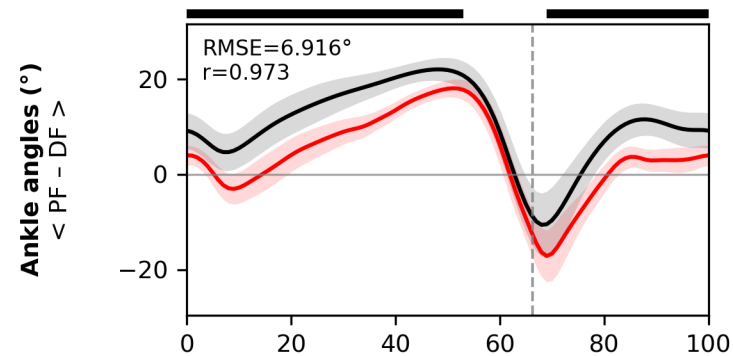
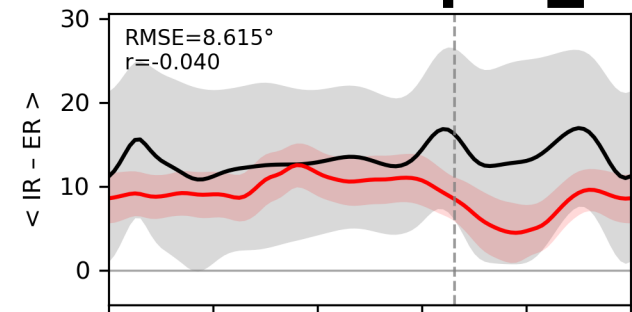
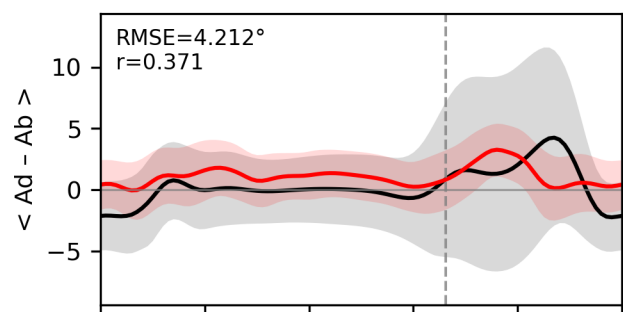
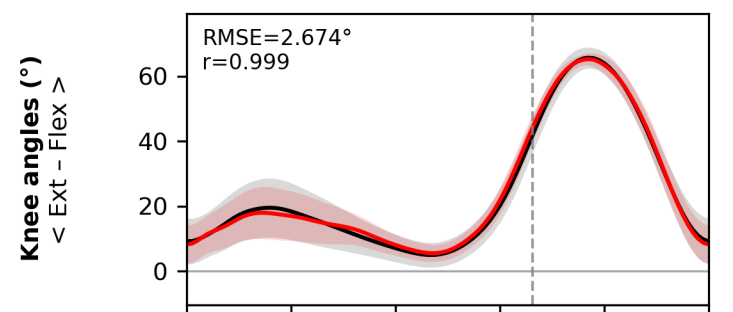
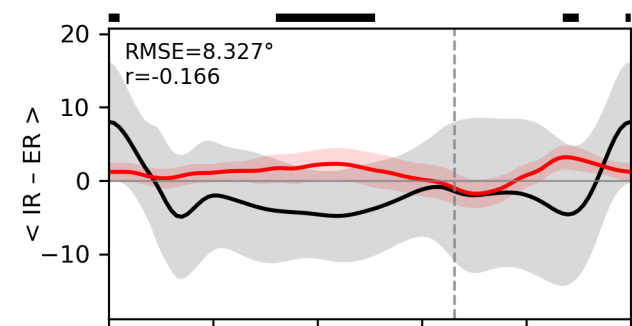
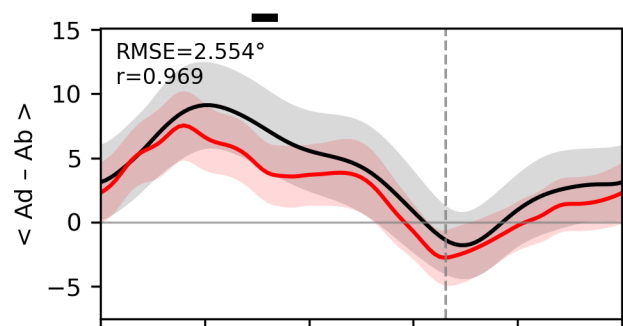
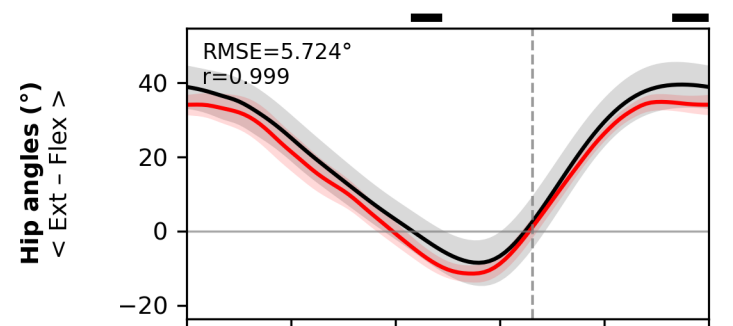
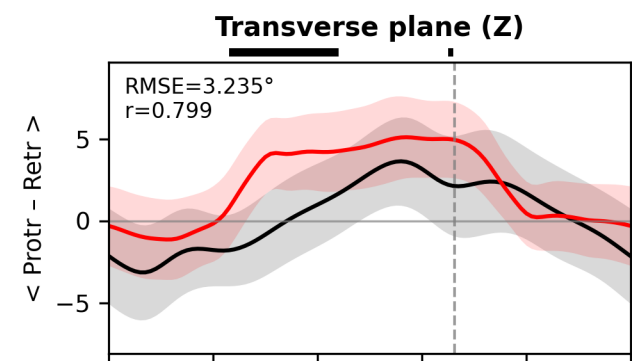
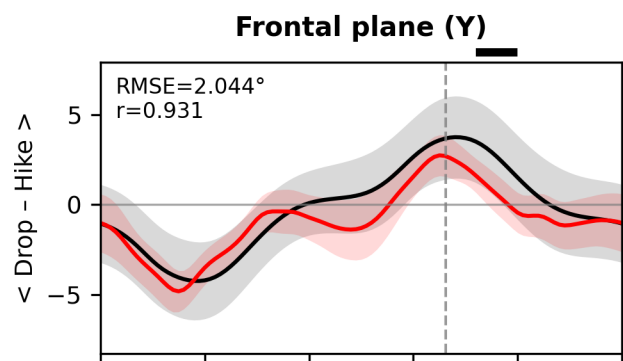
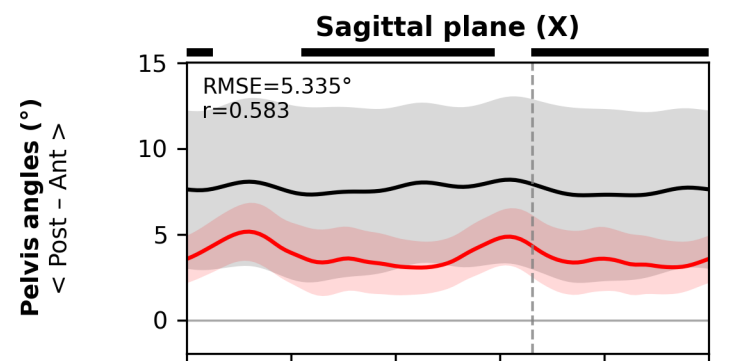
473 The error metrics and statistical evaluations are identical to those described in Table 1.

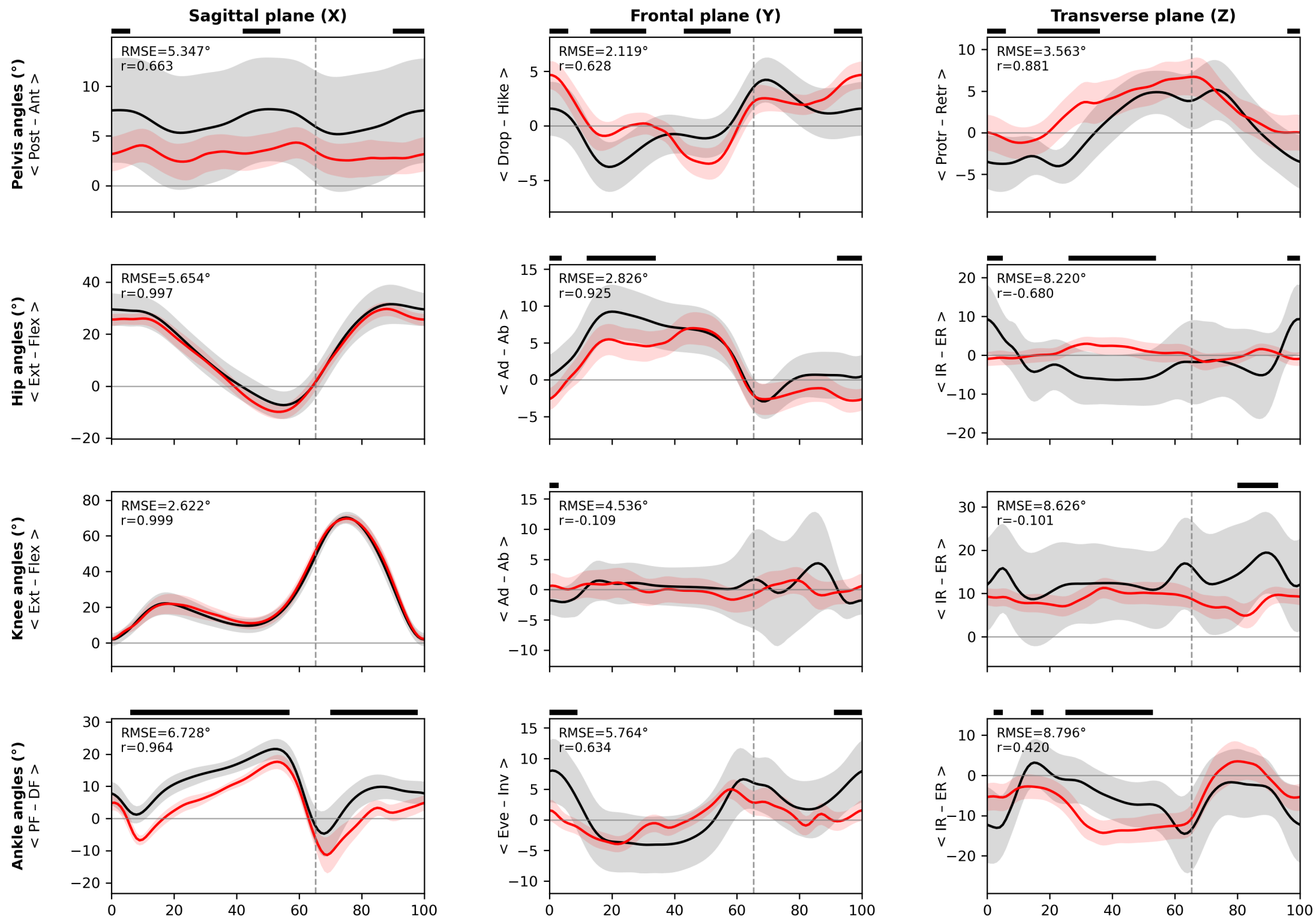
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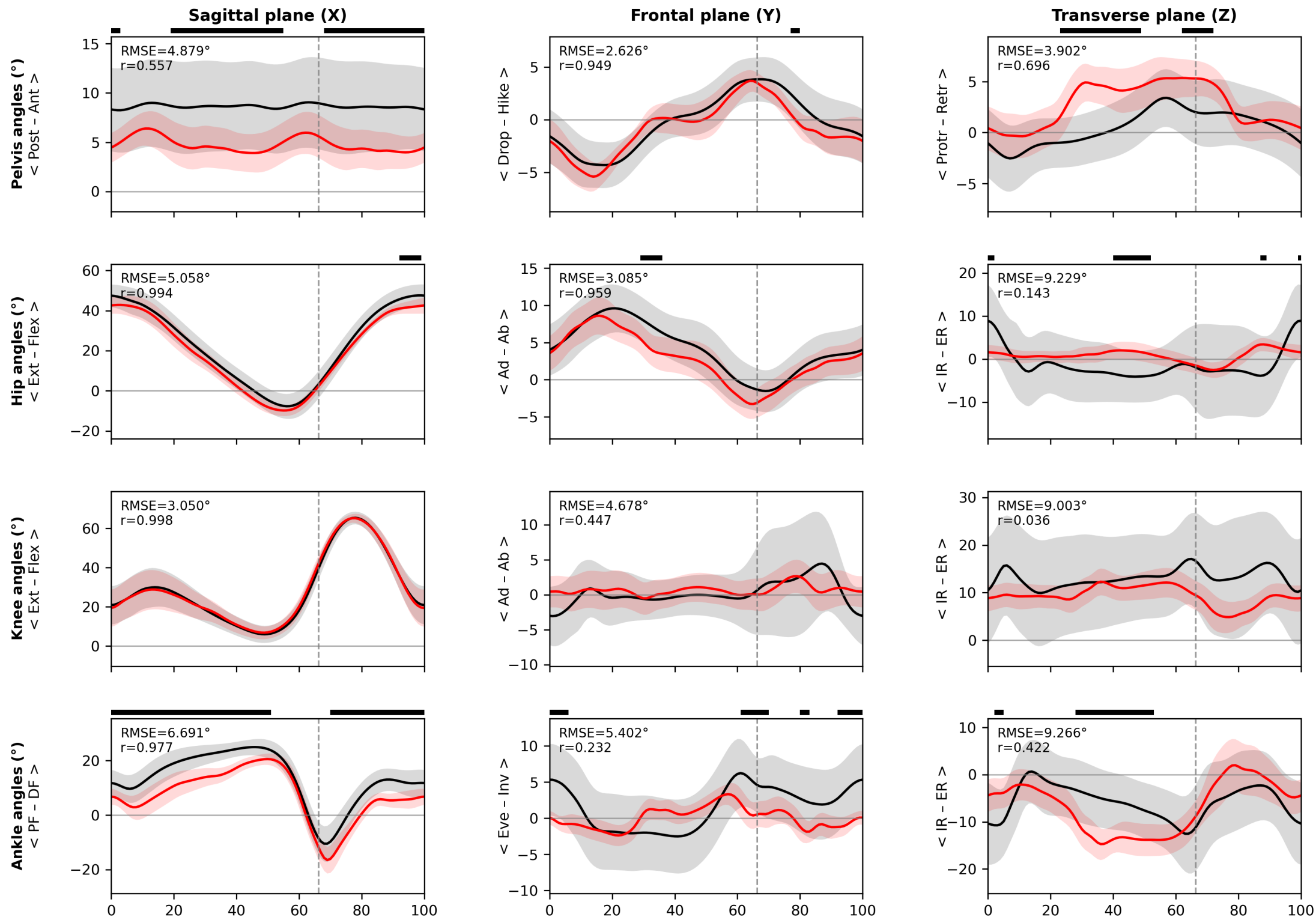
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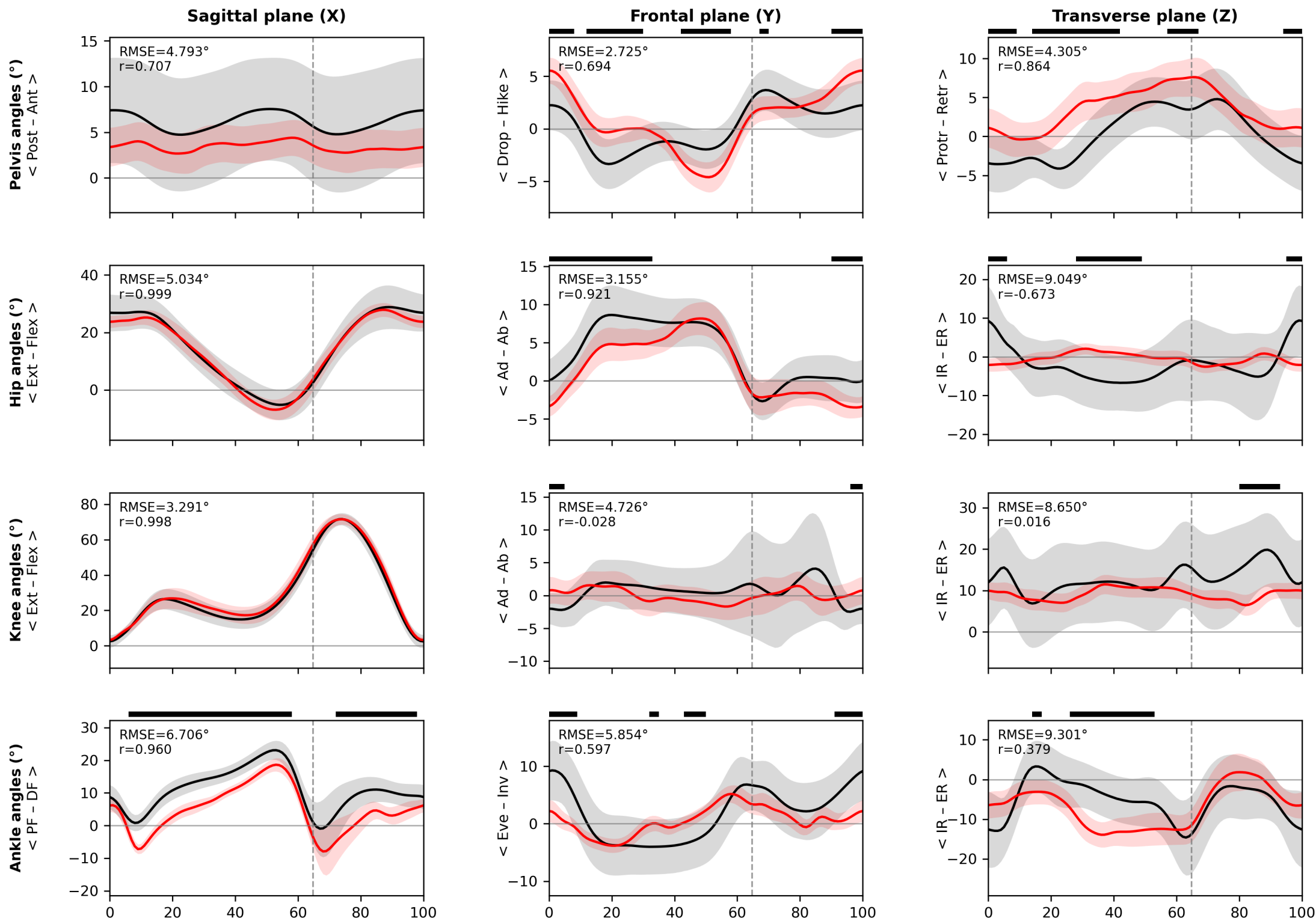












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