The Influence of Occlusion on Markerless Motion Capture Using OpenCap

by

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Markerless motion capture systems such as OpenCap provide a low-cost and accessible alternative to traditional laboratory-based motion capture. This makes them promising for on-location movement analysis, where ideal recording conditions cannot always be achieved. However, reduced visibility of body segments due to self-occlusion, object occlusion or unfavorable camera angles may affect the reliability of the estimated kinematics. This study investigated the influence of occlusion on OpenCap kinematic output using a single-subject repeated-measures design. Six standardized movement tasks were recorded under three visual conditions: an optimal reference condition, a self-occlusion condition and an object-occlusion condition. The exported OpenCap joint-angle trajectories were processed and compared using RMSE relative to the reference condition. The results showed that lower-extremity sagittal-plane tasks remained relatively stable across conditions, while upper-extremity, rotational and supine tasks showed larger deviations and more processing problems. These findings suggest that OpenCap can be useful for on-location movement analysis, but that task selection, camera placement and body-segment visibility should be carefully considered when interpreting kinematic output.

I. Introduction

Accurate measurement of human movement is becoming more important in biomechanics, rehabilitation, ergonomics and sports science. Traditionally, three-dimensional movement analysis is performed using marker-based motion capture systems. These systems can provide highly accurate kinematic data, but they require expensive equipment, dedicated laboratory space, technical expertise and time-consuming marker placement by professionals. This is why tests and measurements of movements are often performed in optimized environments and with optimal focus of the participant. [1].

However, many relevant movement analyses would ideally be performed outside the laboratory. In clinical practice, sports training, occupational ergonomics and field-based research, movement often needs to be assessed on location, for example in a clinic, gym, workplace or home environment. In these settings, the measurement conditions are less controlled. Camera placement may be limited, lighting can be non-optimal and body segments may be partly blocked by the participant's own body or external objects. Therefore, accessible motion capture systems should not only work under ideal laboratory conditions, but also be usable in realistic recording environments [1, 2].

Markerless motion capture has emerged as a promising alternative for these situations, especially because it can reduce the need for laboratory-based equipment and can be used in more practical sport, clinical and field-based settings [1–3]. Instead of using reflective markers attached to the body, markerless systems esti-

mate body pose directly from video recordings. OpenCap is such a system and uses synchronized smartphone videos to estimate three-dimensional body kinematics and dynamics. By combining video-based pose estimation with musculoskeletal modelling in OpenSim, OpenCap can provide joint angles and other biomechanical variables using a relatively low-cost and portable setup [4]. Previous studies have shown that markerless motion capture and OpenCap can produce useful lower-extremity kinematics during tasks such as walking, squatting, hopping, jumping and other functional movements [5–7].

Despite these promising results, real-world use of markerless motion capture remains challenging, because pose-estimation models can be affected by camera placement, visibility of body segments and occlusion [1, 8, 9]. One important limitation is occlusion. Occlusion occurs when a body segment is partly or fully hidden from one or more camera views. This can both be caused by another body segment or by an external objects. In such situations, pose-estimation algorithms must work without the missing information, which may lead to inaccurate joint trajectories or failed processing. Camera viewing angle has also been shown to influence the validity of pose-estimation-based motion analysis [9]. This is especially relevant for upper-extremity and functional tasks, where the arms frequently cross the body, interact with objects or move outside the sagittal plane.

The aim of this study is therefore to investigate how occlusion influences the kinematic output of OpenCap. A single-subject repeated-measures design is used in which six standardized movements are recorded under different occlusion conditions. These tasks include lower-extremity movements, upper-extremity reaching tasks, an object-lifting task and a supine reaching task. The optimal camera condition is used as a reference condition, and the self-occlusion and object-occlusion conditions are compared with this reference.

Because no marker-based motion capture system is used as ground truth, this study does not determine the absolute accuracy of OpenCap. Instead, it evaluates the relative robustness of OpenCap under different visual conditions.

The main research question is: ***How does occlusion influence the usability and consistency of OpenCap kinematic output during lower-extremity, upper-extremity and functional movement tasks?***

By identifying conditions in which OpenCap output remains stable and conditions in which it becomes less reliable, this study aims to support practical recommendations for using OpenCap in on-location movement analysis in further research.

II. Background

A. Video to joint angles

OpenCap does not measure joint angles directly. The system estimates them through a markerless motion capture pipeline. First, two-dimensional body keypoints are detected in each video frame. These keypoints represent visible anatomical landmarks such as the shoulders, elbows, hips, knees and ankles. When the same body landmarks are detected from multiple synchronized camera views, their three-dimensional positions can be reconstructed by triangulation [4]. For further kinematic analysis just landmarks aren't enough. These landmarks need to be converted to more complete anatomical three-dimensional keypoints. This is because else you can't calculate full biomechanical motion such as orientation and rotation. These keypoints are then fitted to a musculoskeletal model using OpenSim and inverse kinematics[4]. The final kinematic output therefore depends on several steps: two-dimensional keypoint detection, multi-view reconstruction, marker-set estimation and musculoskeletal model fitting. This pipeline shows how an error can propagate from a two-dimensional keypoint to calculating wrong angles.

B. Previous validation and interpretation of error magnitude

OpenCap has mainly been validated against marker-based motion capture for lower-extremity and whole-body functional movements. In the original validation study, OpenCap was compared with laboratory-based motion capture and force plate analysis during walking, squatting, rising from a chair and drop jumping [4]. Across these activities, OpenCap reported a mean absolute error of approximately 4.5 degrees for joint angles. This indicates that OpenCap can produce useful kinematic output under controlled conditions and for movement tasks that are similar to those used in validation studies. Other recent OpenCap studies have investigated trunk and lower-limb kinematics during tasks such as squatting, hopping, jumping, side-stepping and other functional movements [6, 7, 10]. These studies support the use of OpenCap for lower-extremity movement analysis, but mainly within task types and recording conditions that resemble the laboratory setup. The interpretation of these errors requires context. In clinical three-dimensional gait analysis, errors below approximately 5 degrees are often considered acceptable for many kinematic variables, although this threshold is not achieved equally for all joints and movement planes [11]. In particular, rotations and out-of-plane movements can show larger errors than sagittal-plane flexion-extension variables [7, 11].

C. Occlusion and camera geometry

Because OpenCap pipeline starts with a two-dimensonal keypoint detection, the output is heavily dependent on how well the body segments are visible in the camera views. Therefore, camera geometry and occlusion are important sources of uncertainty in markerless motion capture. The influence of camera geometry was shown i.e. by Baldinger et al. [9] , who compared OpenPose joint-angle estimations from four camera views with marker-based motion capture during a front-lunge task. They compared 2 cameras behind the participant with two cameras in front, and showed that the pose-estimation was sensitive to camera viewing angle. However, OpenCap validation studies and the camera angle studie do not directly show how consistently OpenCap performs under controlled occlusion conditions.

III. Methodology

A. Study design

The design for this study consists of a single subject with repeated measurements in order to quantify the influence of different kinds of occlusion. Six standardized movements have been chosen, in combination with three occlusion conditions. For each task, one "optimal" condition is used as reference for two other conditions where occlusion was introduced. Each task-condition combination was performed at least 5 times by the subject, resulting in at least a total of 90 trials.

B. Equipment and Software

Data was collected using two iPhones 14 smartphones mounted on tripods. The recording settings were determined by OpenCap, with videos recorded at 60Hz. The exact camera placement is described in Section III.E.

Before data collection, the camera system was calibrated using a 4x5 checkerboard with 35mm squares [12]. Data collection was done on march 23, 2026. The output data of OpenCap was exported as `.mot` files, and further processed using Python 3.13. Main packages used were `NumPy`, `Pandas`, `SciPy` and `Matplotlib`. The Python scripts used available in a GitHub repository: `http://www.github.com/cedekker/thesis_code`.

C. Movement Tasks

Six tasks have been selected. Two tasks focussing on the lower extremity (T1, T2), and three tasks focussing on the upper extremity (T3-T5), and

Table 1. Standardized movement protocol for the six tasks; starting position, movement sequence, and target tempo

Task	Task name	Starting position	movement description	Tempo
T1	Double-leg Squat	Standing, arms crossed	Squat until chair is reached, then back up	2s lowering, 2s up
T2	Sit-to-stand	Standing, arms crossed	sit down and stand up	2s lowering, 2s up
T3	Forward Reach	Standing, arms along body	Reach towards target, hold, arm back to starting position	1s up, 1s holding, 1s back
T4	Overhead reach	Standing, arms along body	Reach up and back to starting position	1s up, 1s back
T5	Object lifting	Standing, arms along body	Pick up and place item, left to right	1s towards object, 2s rotating, 1s to end position
T6	Supine (cross) reach	supine, arms crossed	Touch with right hand left target, touch with left hand right target	1s left, 1s right

one more exploratory supine task (T6). The standardized movements, starting positions, end positions and tempo can be seen in Table 1.

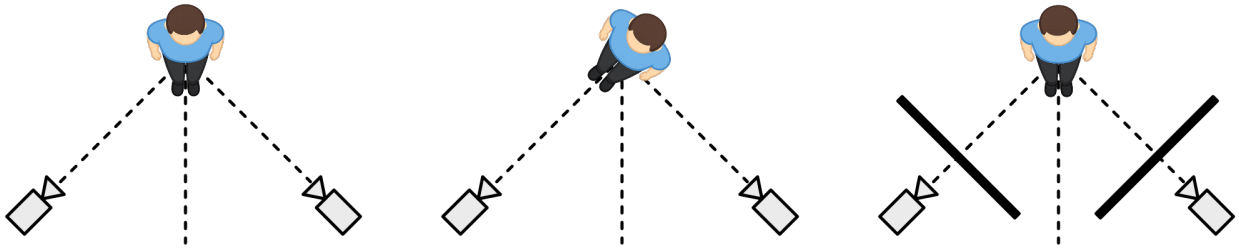
The lower extremity tasks consist of a double-leg (box) squat (T1) and a sit-to-stand movement (T2). The upper extremity tasks are a forward reach towards a shoulder height target in front of the participant (T3), an overhead reach with the right arm (T4) and a object-lifting task (T5). The object lifting consists of grasping a small object (football) at hip height at the left of the participant, and placing in at hip height at the right of the participant. Task 6 was performed in a supine position and the task was to reach across the body towards marked targets.

D. Task selection rationale

Two tasks (T1 and T2) have been chosen to examine how the algorithm of OpenCap deals with the lower extremities. This because the literature extensively validates the markerless motion capture systems on these variables[4, 6, 7, 10]. The first OpenCap algorithm was also primarily trained on walking, sit-to-stand and jumping tasks. Therefore it is suspected that the system can handle occlusions in these tasks very good. The two tasks maybe look alike in movement are very different when looking at it biomechanicall . During the double-leg squat the COM should always stay between the feet, or the parcipant would fall over. During the sit-stand the COM shifts in front of the feet by using the trunk more. Besides the "extra" movement, a chair is also introduced perhaps more challenge for the algorithm.

In the next four tasks (T3, T4, T5 and T6) the limbs that moved and focussed on are primarily in the upper extremities. Because the OpenCap algorithm is updated with more different kind of motion like tennis, dancing, yoga and karate it is suspected it can follow the limbs relatively good.

T3 and T4 are both reaching movements but the movements are in different planes of the body. T4 is expecting to give more self occlusion because the movement of the arm is in the frontal plane. from literature we already expect the movements in the sagittal plane (T3) is better tracked[13] [14].



(a) C1: reference condition (b) C2: self occlusion (c) C3: object occlusion.

Figure 1. The three different camera conditions. a) The reference condition where the whole body can be seen optimal. b) the participant is rotated 45° clockwise so that the body occludes the right side of the body. c) Participant facing as in condition 1, but metal beams are placed in front of both cameras.

T5 is to be a "functional task", and is a example of movements which is done in other literature [15]. The extra difficulty for the algorithm is that the participant is holding an item for a duration of the movement. Also self occlusion is happening because of the rotating torso.

Task 6 is a designed to be an exploratory movement. Since this movement is in a horizontal plane, it would be interesting in how well the OpenCap algorithm is capable of tracking and calculating the rotations. This is also very interesting for further studies where workers are studied in real case scenarios. In example where workers are laying on the ground while fixing or installing hardware.

E. Camera configuration and occlusion conditions

The two smartphones were placed 3,5 m from the position where the subject would be, at a height of 1,2 m. The cameras were positioned symmetrically in front of the camera, each about 45 ° from the frontal plane of the subject. This results of an angle between the two cameras of 90 °. Three different occlusion conditions were then changes by the following changes:

- **Condition 1: Reference** The participant is standing or lying in the direction of the symmetrical axis of the two cameras. The two cameras have therefore perfect view of the full body.
- **Condition 2: Single camera visibility & self occlusion** The participant's body is rotated approximately 45 ° to the right in regards from condition 1. This means that in standing position the participant faces one camera with the other camera perpendicular to its left. In most tasks the right arm will perform the task which introduces occlusion to one of the cameras
- **Condition 3: Object occlusion** In this condition the position of the participant is the same as in condition 1. In this setup there are objects which obstruct the view of the cameras. The initial idea was to place wooden or steel beams in front of the subject, but this was not feasible due to the needed length of the beams for occlusion for both cameras. Therefore, in front of each camera a separate steel structure is placed. While the object occlusion is different for each camera, this setup can still give a good indication of the effect of object occlusion in OpenCap.

F. Trial protocol

Before the measurements started a checkerboard calibration was performed in OpenCap. The checkerboard used for this calibration was a

4x5 checkerboard with 35 mm squares. [12] This checkerboard was recommended by OpenCap. After this calibration one neutral standing trial was recorded, which was used by OpenCap to scale the musculoskeletal model to the participant.[4]

For each movement task and occlusion condition, multiple repeated trials were recorded. To ensure synchronization between the two cameras and the ease for further analysis, each trial followed the same general structure. Every trial started with the participant standing or lying still for approximately 2 seconds. This was followed by a short synchronization movement, consisting of a single hand punch. After the synchronization movement, the participant returned to the starting position and remained stationary for another two seconds before performing the task-specific movement. After completing the movement, the participant again remained still for approximately two seconds before the recording was stopped.

The synchronization movement was included to provide a recognizable peak in the kinematic data. This movement is recommended by OpenCap for synchronization of the two video's, but could also be used during post-processing to identify the start of the relevant movement window and to align repeated trials. The stationary periods before and after the movement were included to ensure that the complete movement cycle was captured and to reduce the risk of cutting off the beginning or end of the movement during trimming.



(a) left camera **(b) right camera**

Figure 2. Screenshots of the camera views in condition 3, with the metal structures in front of the cameras

For each task-condition combination, at least five successful trials were collected, because repeated trials are needed to account for trial-to-trial variability in kinematic movement analysis [16]. A short pause of approximately five seconds was taken between consecutive trials. After each recording, the trial was briefly inspected in the OpenCap interface to verify whether the videos had been uploaded successfully. Since OpenCap processing was performed in the cloud, full inspection of the resulting kinematic data was only possible after processing was completed. If a recording failed to upload or was clearly not processed correctly, additional trials were recorded when possible.

The order of the tasks and conditions was kept consistent throughout the experiment. For each condition, all task repetitions were recorded before moving to the next condition. This minimized the need for changing the location of occlusion objects, chairs and to ensured that the setup remained as consistent as possible within each condition.

G. Data export and processing

The kinematic output from OpenCap was exported as .mot files. These datafiles contain the values for the time and 33 kinematic variables. Based on the movement characteristics of each task a subset of variables were selected which were most relevant to the task. These could have been interested because of the trajectory of the joint or the anatomical plane which they move in. The task-depended variables can be seen in Table 2.

Only trials which were successfully processed by OpenCap and had produced kinematic data which could be used for analysis were used. This meant that if the kinematic output was just a part of the movement or had no clear similarities to the actual movement, this trial would not be further used and analyzed. Each trial would be trimmed just after the synchronisation movement which is explained in subsection III.F because this was not part of the task-movement.

For each task, one trial from condition 1 was selected as the reference trial for temporal alignment of the other trials of this task. First, the movement was isolated by using task-specific reference variable. This variable had to have a clear peak in the movement pattern. The selection of this reference variable was chosen based on visual inspection of the multiple signals of the movement.

After one trial of the task was trimmed the other trials were aligned using cross-correlation. For each task, a correlation variable was selected that showed a clear and distinctive trajectory, which was hopefully not affected by the possible occlusion. The cross-correlation between the reference trial and the trial to be aligned was calculated by equation 1, where k is the lag, a and v the two signals and n the number of datapoints. The lag which resulted in the biggest correlation is used to shift the signal. Both the reference variable and sync variable for each task can be seen in table 3. These variables were not always the same within a task, because the initial trimming step required a variable with a distinct peak in the movement, while the alignment step required a clear and repeatable variable trajectory across the full movement.

$$c_k = \sum_n a_{n+k} \cdot \overline{v_n} \tag{1}$$

All trials within the same task are trimmed to the same number of samples. No resampling or time normalization was applied. This ensured that the original OpenCap time series were preserved. Dynamic time warping was also considered as an alternative method for alignment, but was not used because it locally stretches or compresses the time axis. Since the aim was to compare the original OpenCap trajectories, cross-correlation-based alignment was preferred.

H. Statistical analysis

Firstly for each selected kinematic variable, the variability within each task condition combination is calculated. This is done by calculating the standard deviation across each trial in this task-condition combination. Firstly the mean trajectory is calculated using Equation 2, where μ_t is the mean at at timesample t, n is the number of trials for the condition of the task, $y_{i,t}$ is the value in trial i at timesample t.

Then the standard deviation is calculated with the use of Equation 3.

$$\mu_t = \frac{1}{n} \sum_{i=1}^{n} y_{i,t} \tag{2}$$

$$SD_t = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (y_{i,t} - \mu_t)^2} \tag{3}$$

For further analysis also the Root Mean Square Error (RMSE) is used to quantify the effect of the different type of occlusion. For each trial in a task the RMSE was calculated in respect to the mean of the trials of condition 1. firstly the reference trajectory of the task was calculated by Equation 4, with N_{C1} the number of trials in C1. Note that this is the same as equation 2 for condition 1, but this is also the reference for the other conditions it the task.

Then the RMSE for each selected kinematic variable for each trial is then calculated. The RMSE will be calculated with the Equation 5, where T is the number of time samples and $(y_{i,t} - r_t)^2$ is the squared error between the trial value y_i and the reference value r_t. A lower RMSE is an indication that the trial trajectory was closer to the reference trajectory of condition 1.

Lastly, for each task-condition-variable the mean RMSE and the standard deviation of the RMSE across the trials was calculated with Equation 6 and Equation 7 respectively.

$$r_t = \frac{1}{N_{C1}} \sum_{i=1}^{N_{C1}} y_{i,t} \tag{4}$$

$$\text{RMSE}_i = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (y_{i,t} - r_t)^2} \tag{5}$$

$$\overline{RMSE} = \frac{1}{n} \sum_{i=1}^{n} RMSE_i \tag{6}$$

$$SD_{RMSE} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (RMSE_i - \overline{RMSE})^2} \tag{7}$$

The mean RMSE was used to quantify the average deviation from the reference condition, while the standard deviation of the RMSE was used to describe the between-trial variability of this deviation.

The RMSE will be used as a benchmark to determine how well the accuracy is of the OpenCap system. From literature a benchmark is set of RMSE of 5° or lower is considered good enough for use for further kinematic analysis [11] [7] [17]. A RMSE value between 5° and 10° can be used with caution. The measurements are sometimes usable for motion analysis but not for further kinematic analysis. This also depends on the total range of motion and depending a correlation between the trials (is the RMSE consistently giving the same error, which would mean a lower SD). A RMSE higher than 10° is seen as an too big of an error for reliable further clinical usability.

Furthermore it must be said that these RMSE values are against C1, and not a ground truth. This is a relative error.

Condition 2 and 3 are expected to produce higher RMSE values than condition 1. To test if the difference is statistically significant a two-sided Welch's independent t-test was performed for comparing C2 with C1 and C3 with C1. The Welch's test was selected because the number of usable trials and variances could be different in each condition.

IV. Results

A. processing succes

In total 117 trials have been recorded with a minimum of 5 trials per condition per task. Some tasks/conditions combination have up to 7 trials. After all recordings were done it was checked if the recordings are processed in a good manner by OpenCap. When a trial is red in this figure it means OpenCap was not able to process the trial videos. This happened in two trials, both in the object-lifting task. OpenCap unfortunately does not give insight in why it was not processed correctly. In addition 10 trials were processed by OpenCap but were not usable for further analysis. In these outputs there is just a part of the movement processed, or the output was so greatly distorted that clear comparison with the other trials was not possible. All other trials were processed correctly by OpenCap. The processing succes can be seen in Figure 3.

The processing success is different per task.

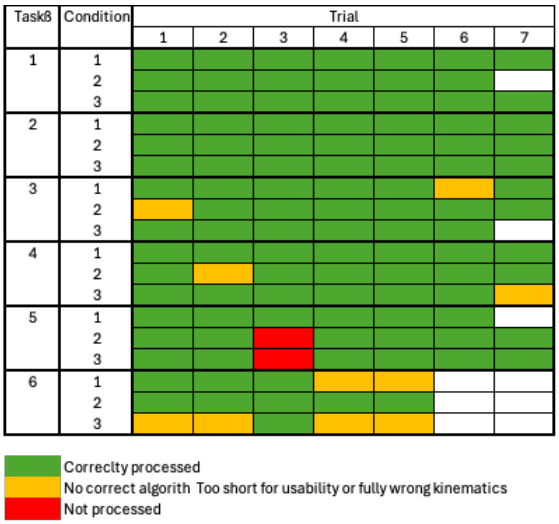


Figure 3. Trial succes

Both lower extremity tasks showed the highest success rate, with all trials successfully processed. The forward reach and overhead reach tasks showed respectively 1 and 2 unusable trials. The supine reach task showed the most unusable trials with only 9 of the 15 trials successfully processed. Condition 3 in combination with the supine reach only resulted in one usable data output, which limits the final RMSE interpretation for this condition-task combination.

B. RMSE patterns

All correctly processed trials were then processed as explained in subsection III.G. The mean RMSE and standard deviation of the RMSE for each task, condition and selected kinematic variable are shown in Figure 4. The numerical values can be seen in Table 4 in Appendix C.

Every trial for the selected variables in each task can be seen in Appendix E.

In these figures the light grey lines represent the individual trials. The darker blue line is the average trajectory of the trial in the specific condition, while the dotted red line represents the average trajectory of the first condition of the respective task.

In Figure 4 the calculated mean RMSE of each condition in respect to the mean trajectory of condition 1 each shown as a bar diagram. In each subfigure the blue, the orange and the green represent the different conditions 1, 2 and 3 respectively. The calculated SD is also shown in this figure with by the error bars. While Figure 4 gives a good overview of the RMSE and SD, all values are also shown in Table 4 in Appendix C. The RMSE values represent the deviation of each trial in respect of the mean of condition 1 for that task.

Therefore, the values for condition 1 in each task is not zero, since these are compared to the mean of this same condition.

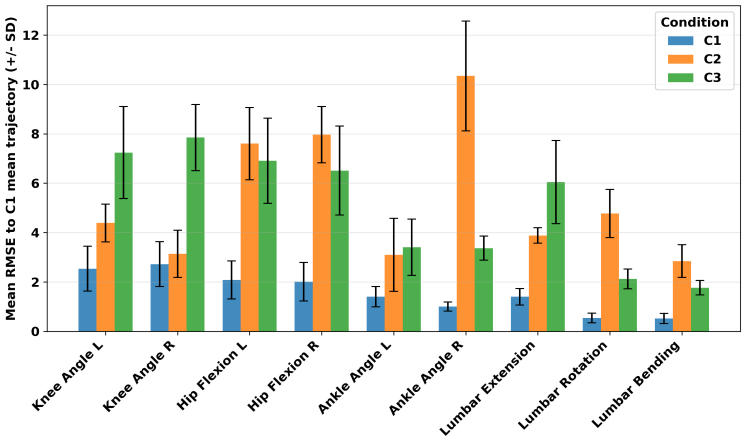
Across most tasks, condition 1 showed the lowest RMSE values and the lowest standard deviation. Conditions 2 and 3 generally increased both the RMSE and the standard deviation from the reference trajectory, but the magnitude depends on the task and variable. in general, the lower-extremity tasks (double-leg squat and sit-to-stand) give lower RMSE values than the upper-extremity tasks(reaching, overhead reach and object-lifting).

In the overhead reach the highest RMSE values are seen in the upper-extremity variables and especially in the arm rotations and elbow flexion. More detailed trial data can be seen in Appendix E. In these graphs the trials are shown per condition for each variable. The standard deviation is also shown by a bandwidth color.

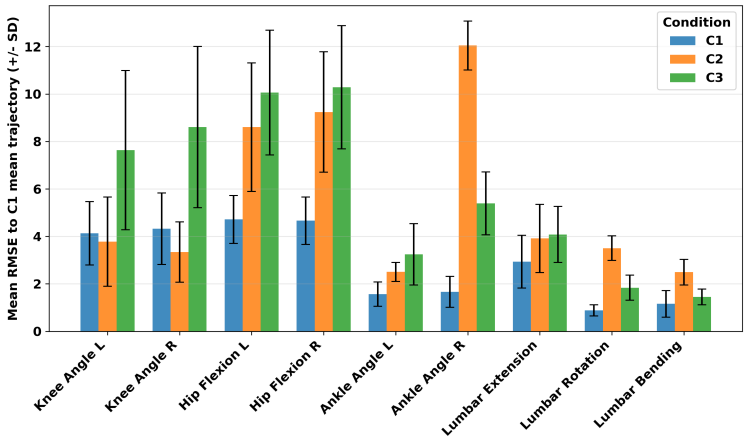
C. Lower-extremities

Looking at the double-leg squat, all selected variables in condition 1 had a RMSE below 3 degrees. The largest increase in condition 2 is the right ankle, which increased to over 10 degrees. This is the ankle which is occluded by the left leg. Hip flexion also increased in condition 2 for both sides to 7.60° and 7.96°, left and right respectively. In condition 3 higher RMSE values were found again for the hip flexion but also for the knee (both left and right, 7.24° and 7.85° degrees respectively). The right ankle and hip flexion offset in condition 2 can be clearly seen in Figure 5a and 5b.

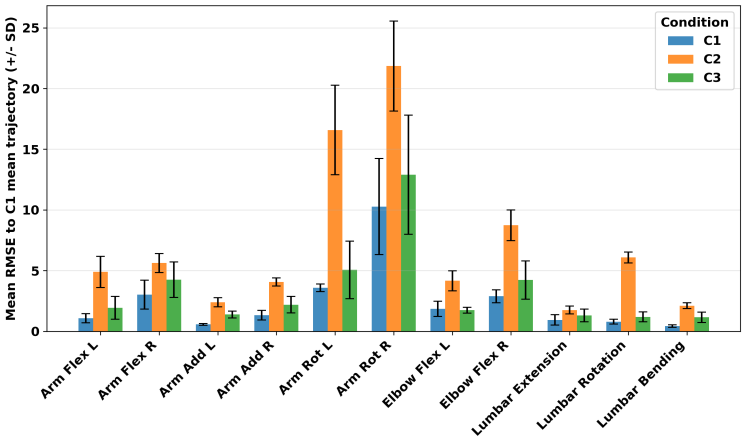
Task 2, the sit-to-stand task, shows a similar pattern as the double-leg squat. In condition 1, all selected variables had RMSE values of lower than 5°. Condition 2 had the highest RMSE value for the right ankle (12.04°) but also a high RMSE value for the hip flexion. 8.6° and 9.24° for left hip flexion and right hip flexion respectively. In condition 3, the hip flexions left and right, knee angles, left and right, and right ankle all showed higher RMSE values. Which is the same pattern as for the double-leg squat. The highest RMSE values for condition 3 were found for the hip flexion left, 10.06° and hip flexion right, 10.28°. Again these angle offsets of the ankle and hip can be clearly seen in Figure 6a and 6b.



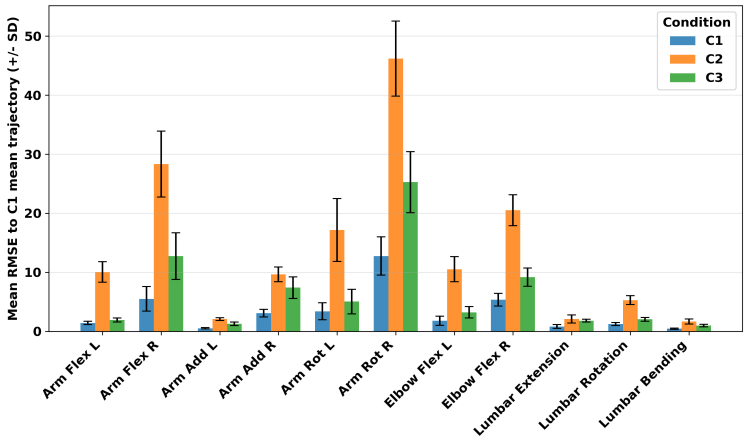
(a) Task 1: Double-leg squat



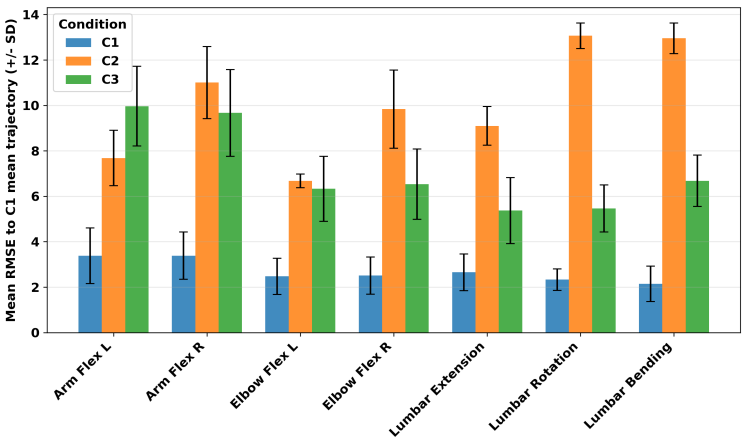
(b) Task 2: Sit-to-stand



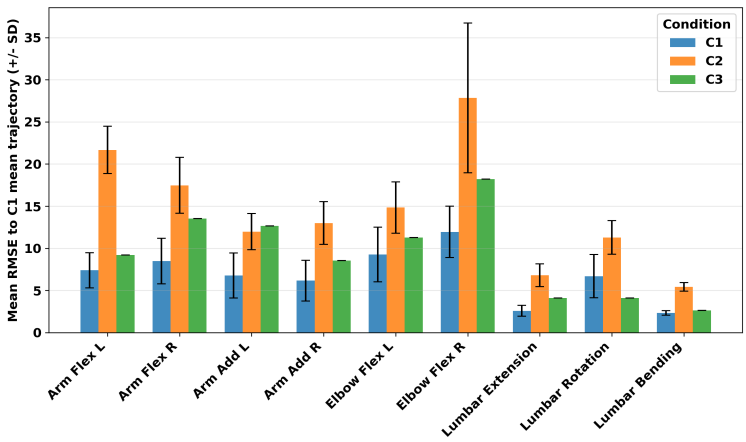
(c) Task 3: Forward reach



(d) Task 4: Overhead reach



(e) Task 5: Object lifting



(f) Task 6: Supine reach

Figure 4. RMSE for each selected variable for the six movement tasks. Bars represent the mean RMSE relative to the reference trajectory. Error bars indicate the standard deviation.

D. upper-extremity reaching tasks

The forward reach tasks showed low RMSE values for most variables in condition 1. condition 2 and 3 showed a little higher RMSE values but most stayed under 5 °. Exceptions are the arm rotations.

In condition 1 already the right arm rotation has an RMSE of 10.28 degrees. This increases in condition 2 to 21.85 degrees and in condition 3 to 12.90°. In condition 2 also the left arm rotation increases to 16.59° and in condition 3 to 5.09°. in Figure 7c it can clearly be seen that for condition 2 this RMSE error is clearly a computational error. OpenCap systematically computes the rotation of the arms incorrectly. This also happens with the lumbar rotation in condition 2. The RMSE value jumps from 0.79° in condition 1 to 6.08° in condition 2. In Figure 7e the offset is seen clearly.

The overhead reach showed much larger RMSE values than de forward reaching task. In condition 2, there are several variables exceeding the 10° RMSE. The largest RMSE was found in the right arm rotations with 46.2° in condition 2. Right arm flexion also increased to a RMSE of 28.32° in condition 2. Figure 8c shows that the mean of the movement in condition 2 is a bit shorter, but the standard deviation in condition 2 is also a lot higher. Condition 3 showed also higher RMSE values than condition 1, especially for the right arm rotation and right arm flexion, 25.27° and 12.75° respectively.

E. Object-lifting and supine reach tasks

The "functional" task, the object-lifting task showed low RMSE values for all variables in condition 1. The values are between 2.15° and 3.38°. In condition 2 and 3 the errors increased for both the upper-extremity and lumbar variables. In condition 2, the largest RMSE value were found for lumbar bending and lumbar rotation, 12.95° and 13.07° respectively. In Figure 9c it can be seen where this error comes from. While the lumbar rotation and lumbar bending are lower in condition 2 than 1, the extension is a lot higher. All other variables in condition 2 have a RMSE between 6.68° and 11°. In condition 3, the RMSE values for all variables are lower than in condition 2. But all values remain between 5.37° and 9.97°.

The supine reach, even in condition 1. Most variables were higher than 5° and the right elbow flexion even higher with 11.94°. In condition 2, the only lower RMSE values were lumbar bending and extension (in respect to the mean of condition 1) with 5.42° and 6.80° respectively. The higher values in condition 2 were the right elbow flexion with 27.84° and left arm flexion with 21.68°. Condition 3 showed better results for all variable except for the left arm adduction. Because there was only one trial which was processed correctly, no standard deviation could be calculated for this condition. These results for condition 3 in this task can therefore not give a reliable estimation of between trial performance.

F. Statistical comparison of RMSE values

The Welch's test support the RMSE results seen in Figure 4. The complete statistical results for the comparison between the conditions can be seen in Appendix D, with the comparison of C2 with C1 in Table 5 and C3 with C1 in Table 6.

For the lower extremity tasks one of the higher RMSE differences was the right ankle in C2 ($\Delta RMSE = 10.38°, (t = 10.27), (p < .001)$) for T1 and ($\Delta RMSE = 9.34°, (t = 22.55), (p < .001)$) in T2. Regarding the upper extremity tasks, C2 had a statistically higher RMSE during T3 and T4, especially for the variables of arm rotation and elbow flexion. In the object-lifting task, both C2 and C3 showed significantly higher RMSE with C2 showing the largest differences for lumbar bending and rotation. For the supine reach there was no statistically comparing possible between C3 and C1 due to only one usable C3 trial.

V. Discussion

A. Main Findings

The goal of this thesis was to investigate how occlusion influences the usability and consistency of OpenCap kinematic output, and how this differs between lower-extremity, upper-extremity and functional tasks. The results show that this influence is strongly task-dependent and also depends on which kinematic variables are selected. In general, the lower-extremity tasks showed lower RMSE values than the upper-extremity tasks. Movements in the sagittal plane also seemed more robust to occlusion than rotations and movements in other planes. This can be seen especially in the supine reach task, where there were more processing problems and higher RMSE values.

For both the double-leg squat and sit-to-stand task, most variables showed low RMSE values in the reference condition. When occlusion was introduced, the RMSE values increased for some variables, especially for the right ankle during self-occlusion. However, the movement trajectories were still clearly recognizable and all trials were processed successfully. This suggests that OpenCap can still be useful for relatively simple upright lower-extremity tasks, even when the visual conditions are not optimal. The low RMSE values are consistent with previous lower-extremity OpenCap validations [4].

In contrast, the upper-extremity tasks were affected more by occlusion. The forward reach task showed good results for several variables, but not for arm rotation. Especially in condition 2, where one camera had a less optimal view of the reaching arm, OpenCap had more difficulty estimating the rotation of this body segment. The overhead reach showed the largest deviations. In this task, especially right arm rotation and right arm flexion had high RMSE values in the self-occlusion condition. The object-lifting task was also affected by occlusion, mainly in the lumbar rotation, lumbar bending and arm flexion variables.

The supine reach task showed both high RMSE values and a lower processing success rate. This suggests that this task was difficult for OpenCap, even in the reference condition. A possible explanation is that OpenCap is more robust for upright movements than for movements performed in a lying position. In a supine position, the body orientation relative to the cameras is different from the standard upright movements for which OpenCap is mostly used.

Overall, these results suggest that OpenCap is relatively robust for upright lower-extremity movements, especially when these movements are mainly performed in the sagittal plane. However, the output becomes less consistent for upper-extremity tasks, rotational movements, object-interaction tasks and supine movements. Therefore, OpenCap output under occlusion should not be interpreted as generally reliable or unreliable, but should be judged per task, per condition and per selected kinematic variable.

B. Processing success as a measure of usability

Besides RMSE, processing success is also an important outcome in this study. The fact that a trial cannot be processed, is processed only partly, or produces clearly distorted kinematics is a clear sign how well OpenCap can handle certain movements.

The lower-extremity tasks had the highest processing success. All squat and sit-to-stand trials resulted in usable kinematic output. This supports the idea that OpenCap is most robust for upright functional movements that are similar to tasks used in previous validation studies, such as squatting, sit-to-stand movements, jumping and walking.

The upper-extremity tasks had a lower processing success. Especially for rotating segments. The supine reach task showed the clearest processing limitations. Several trials were not usable, and in the object-occlusion condition only one usable trial remained. Besides that there was no RMSE to be calculated, it also shows that a lying

down position roll task is not (yet) suitable for OpenCap.

The results of this thesis suggest that processing reliability decreases when movements becomes less similar to standard upright full-body tasks.

C. Effect of self-occlusion and object occlusion

Both the conditions, self-occlusion and object occlusion influenced OpenCap output, but not in the same way. In this study setup, condition 2 did not only introduce self-occlusion, but also changed the camera viewing angle. The participant was rotated approximately 45 degrees relative to the reference condition. As a result, one camera had a more frontal view, while the other camera had a more lateral view. This reduced the visibility of some segments, especially during tasks where the right part of the body was occluded by the left part of the body for one camera.

A clear example in the lower-extremity tasks was the right ankle angle during the squat and sit-to-stand task. In condition 2, the right ankle showed a systematic offset compared with the reference condition. Which was probably caused by the right ankle being hidden from one camera view. This shows that even when the overall movement is still processed successfully, occlusion of a specific body segment can still result in a clear error for the corresponding joint angle.

For the forward and overhead reach, the problem was slightly different. The high RMSE values for right arm rotation and right arm flexion were probably not only caused by self-occlusion, but also by the camera angle. In this task, The arm was rotating along the viewing axis of on of the camera views. This probably made it more difficult for OpenCap to reconstruct the three-dimensional position and rotation of the arm segment. This is especially important for rotational variables. For flexion or adduction, the displacement of the segment is often clearly visible in the image plane. For rotation around the long axis of the arm, however, the visual change can be much smaller in one camera view. As a result, OpenCap may still detect the arm segment, but estimate its rotation less consistently.

In the object-occlusion condition, the participant position was the same as in the reference condition, but structures were placed in front of the cameras. The effect of this condition depended again on the tasks. In the lower-extremity tasks, object occlusion increased RMSE values for several hip and knee variables. This may be related to partial obstruction around the pelvis and lower body. In the upper-extremity tasks, object occlusion generally caused smaller deviations than condition 2, although several arm variables still showed increased RMSE values. Looking back at Figure 2, we can see that the hips are clearly occluded for the right camera, which can lead to the offset of hip flexion in the sit-stand task.

This suggests that object occlusion should not be interpreted only by the size of the object in the image, but also by its location relative to the body. If the object blocks a part of the body that is not important for the selected variables, the influence may be limited. However, if the object obstructs an important anatomical landmark or a region where OpenCap estimates virtual landmarks, the effect may be much larger. In that case, even a relatively small occlusion could affect the reconstructed three-dimensional keypoints and the final joint-angle output.

Therefore, these results show that the influence of object-occlusion depends on the location of the occlusion relative to the movement being analyzed. In this study the object occlusion was less disruptive than condition 2, but it still reduce the consistency of the output considerable.

D. Differences between lower-extremity and upper-extremity tasks

The results showed a clear difference between lower-extremity and upper-extremity tasks. The lower-extremity tasks were more consistent across conditions, while the upper-extremity tasks showed larger deviations, especially for rotation

variables.

One explanation is that the lower-extremity tasks were mostly performed in the sagittal plane and had relatively constrained movement patterns. During squatting and sit-to-stand movements, hip, knee and ankle flexion-extension follow predictable trajectories. These movements also resemble tasks that OpenCap has been trained on and have previously been used to validate OpenCap and other markerless motion capture systems. Therefore, the pose-estimation and musculoskeletal modelling pipeline may be better suited to these movements.

The upper-extremity tasks were less constrained and involved more complex three-dimensional motion. Arm rotation, shoulder flexion, shoulder adduction and elbow flexion may be more sensitive to small errors in estimated keypoint positions. This was especially visible in the arm rotation variables, which showed high RMSE values even in some reference-condition trials. This suggests that arm rotation may be difficult to estimate consistently with OpenCap, even in a occlusion free condition.

The overhead reach was the clearest example of this problem. In this task, the arm moved upward through the frontal plane. In condition 2, this movement was less favourable for the camera setup, because one camera mainly captured the arm from the front while the other camera captured more of a side view. During the movement, the arm also rotates around its longitudinal axis. This rotation is difficult to estimate from video, because it cannot be determined clearly from the position of the shoulder, elbow and hand alone. As a result, OpenCap may still detect the arm segment, but estimate its rotation less consistently. This probably contributed to the large deviations in right arm rotation and right arm flexion during the overhead reach.

The object-lifting task added another type of complexity. This task combined arm movement, trunk rotation, bending and extension and interaction with an external object. The increased RMSE values for lumbar bending, lumbar rotation and arm flexion suggest that combined functional movements are more challenging than isolated single-joint or single-plane tasks. For practical applications, this means that OpenCap may be useful for analysing broad movement patterns during functional tasks, but that specific joint-angle interpretation should be done carefully when occlusion and rotation of the body in respect to the cameras are present.

E. Interpretation of RMSE values

The RMSE values in this study should be interpreted as relative deviations from the reference condition, not as absolute accuracy values. No marker-based motion capture system, which is seen as the gold standard, was used as a ground truth reference. Therefore, this study cannot determine whether the reference condition represented the true joint kinematics. Instead, the reference condition was used as the most visually optimal OpenCap condition, and the other conditions were compared with this baseline.

This distinction is especially important for tasks that already showed high RMSE values in condition 1. For example, the supine reach task and several arm rotation variables showed relatively high deviations even in the reference condition. This indicates that task complexity itself influenced the consistency of OpenCap output. In cases like this, high RMSE values in the occlusion conditions may reflect both the effect of occlusion and the general difficulty of the task for OpenCap.

The 5-degree benchmark was used to help interpret the magnitude of the deviations, but it should not be treated as a strict pass-or-fail threshold. In previous literature, errors below approximately 5° are often considered acceptable for many kinematic variables. However, acceptable error depends on the joint, movement plane and range of motion. A 5-degree error may be acceptable for a movement with a large range of motion, but may be problematic for a small rotational movement. Therefore, RMSE values

in this study should be interpreted together with the trajectory plots and standard deviations.

F. Methodological considerations and limitations

Several methodological choices should be taken into account. First, this study used a single-subject repeated-measures design. This allowed a controlled comparison between visual conditions, because participant characteristics were kept constant. However, it also limits the generalizability of the results. Different participants may produce different results because of differences i.e. body proportions.

Second, the study did not include marker-based motion capture as a ground truth system. As a result, the study cannot make conclusions about the absolute validity of OpenCap under each condition. The results only show how much the OpenCap output changed relative to the reference condition. Future studies should compare occlusion conditions directly with marker-based motion capture to determine whether the observed deviations correspond to true kinematic errors. that would also mean that is possible to compare the same trial instead of between trials.

Third, the order of tasks and conditions was kept consistent throughout the experiment. This made the setup more practical and reduced the need to reposition objects and cameras. Although it is not clear in the trial data, it may have introduced effects. For example, the participant may have become more familiar with the tasks over time, or fatigue may have influenced later trials. Future studies could randomize the order of tasks and conditions to reduce this potential bias.

Fourth, the severity of occlusion was not quantified objectively. The object-occlusion condition was created using physical structures in front of the cameras, but the exact amount of segment obstruction was not measured. Future studies could quantify occlusion by determining the percentage of frames in which key body landmarks are visible, or by systematically masking specific body segments in the video data.

Fifth, only one two-camera setup was tested. The results therefore apply to this specific camera configuration and cannot automatically be generalized to other OpenCap setups. Future work should investigate whether different camera angles, camera heights or additional cameras improve robustness during upper-extremity, rotational and supine movements.

Sixth, it was chosen not to use dynamic time warping for the final analysis. Dynamic time warping could have aligned the trials more closely by locally stretching or compressing the time axis. This may have reduced the RMSE values, especially when differences between trials were partly caused by small variations in movement speed. However, this would also change the original time structure of the OpenCap output and it is possible that it would mask OpenCap errors. Since the goal of this study was to compare the kinematic trajectories as they were produced by OpenCap, only cross-correlation was used to correct for a global time shift between trials.

This means that part of the RMSE may be caused by timing differences between trials, and not only by differences in the estimated joint angles. For example, if one trial was performed slightly faster in the middle of the movement, cross-correlation would not fully correct for this. Future studies could use dynamic time warping as an additional tool but is also not a perfect tool. While DTW could overlay the trajectories better, it may also mask errors. So this tool should be used carefully.

G. Practical implications

The findings of this study suggest that OpenCap can be useful for on-location movement analysis, but that its output should be interpreted in relation to the task and recording condition. For upright lower-extremity tasks, OpenCap produced relatively consistent kinematic trajectories, even when some occlusion was present. For upper-extremity, rotational, object-interaction

and supine tasks, the output was less consistent and more likely to contain large deviations or unusable trials.

For practical use, this means that camera placement should prioritize visibility of the main moving segments. Single-camera side views or conditions where the observed limb is hidden by the body should be avoided. Object occlusion should also be minimized, especially near body segments that are central to the variables of interest. When occlusion cannot be avoided, OpenCap output should be checked visually and interpreted cautiously, especially for rotation variables and complex functional tasks.

VI. Conclusion

This study investigated how occlusion influences the usability and consistency of OpenCap kinematic output. The results show that the effect of occlusion is not the same for every task or variable. OpenCap gave the most consistent results during the upright lower-extremity tasks. For the squat and sit-to-stand task, most trajectories were still clearly recognizable, even when occlusion was introduced.

The upper-extremity tasks were more affected by occlusion. Especially the overhead reach showed large deviations in arm rotation and arm flexion. The object-lifting task also showed increased RMSE values, mainly in the arm and lumbar variables. The supine reach task was the most difficult task for OpenCap, because several trials could not be used and the RMSE values were already high in the reference condition.

These results suggest that OpenCap can be useful for on-location movement analysis, but that the output should always be interpreted in relation to the task and camera setup. Camera placement should focus on keeping the important body segments visible. Conditions where one camera mainly has a side view, or where the moving limb is hidden by the body, should be avoided when possible.

It is important to note that this study did not use marker-based motion capture as a ground truth system. Therefore, the RMSE values do not represent absolute accuracy, but only the deviation from the reference condition. Future studies should compare occlusion conditions directly with marker-based motion capture, use multiple participants and test different camera setups. This would give a better understanding of when OpenCap can be used reliably in real-world movement analysis.

Declaration of AI use

During the process of this study ChatGPT (OpenAI) was used for brainstorming the layout and chapter structure and to help with grammar corrections. Codex (OpenAI) was used to clean up and improve the structure of the python code.

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VII. Appendix

A. Task reference

Table 2. Selected OpenCap variables per task and correspondent OpenCap references. A cross means that this variable was selected for analysis for this task.

		Double squat	Sit-to-stand	Forward reach	Overhead reach	Object lifting	Supine reach
Movement	**OpenCap reference**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**
Ankle dorsiflexion	`ankle_angle_l`	×	×				
	`ankle_angle_r`	×	×				
Knee flexion	`knee_angle_l`	×	×				
	`knee_angle_r`	×	×				
Hip flexion	`hip_flexion_l`	×	×				
	`hip_flexion_r`	×	×				
Shoulder adduction	`arm_add_l`			×	×		×
	`arm_add_r`			×	×		×
Shoulder flexion	`arm_flex_l`			×	×	×	×
	`arm_flex_r`			×	×	×	×
Shoulder rotation	`arm_rot_l`			×	×		
	`arm_rot_r`			×	×		
Elbow flexion	`elbow_flex_l`			×	×	×	×
	`elbow_flex_r`			×	×	×	×
Lumbar extension	`lumbar_extension`	×	×	×	×	×	×
Lumbar rotation	`lumbar_rotation`	×	×	×	×	×	×
Lumbar bending	`lumbar_bending`	×	×	×	×	×	×

B. Process variable

Table 3. Chosen trimming variables and correlation variable used for syncing the trials per task

Task	trimming variable	syncing variable
T1	pelvis_ty	pelvis_ty
T2	pelvis_ty	pelvis_ty
T3	arm_flex_r	arm_rot_r
T4	arm_rot_r	arm_add_r
T5	lumbar_rotation	lumbar_bending
T6	arm_add_r	arm_add_r

C. RMSE and SD

Table 4. Mean RMSE and standard deviation (SD) of the RMSE across trials for each selected kinematic variable, task, and occlusion condition. Cell colours indicate RMSE values below (5°) (green), from (5°) to (10°) (orange), and above (10°) (red).

Task	Selected variable	RMSE			SD		
		C1	C2	C3	C1	C2	C3
T1: Double squat	ankle l	1.40	3.09	3.41	0.41	1.48	1.14
	ankle r	1.01	10.34	3.37	0.18	2.22	0.49
	hip flexion l	2.08	7.60	6.91	0.77	1.46	1.72
	hip flexion r	2.01	7.96	6.51	0.78	1.14	1.80
	knee l	2.54	4.39	7.24	0.91	0.77	1.86
	knee r	2.72	3.14	7.85	0.91	0.96	1.34
	lumbar bending	0.52	2.84	1.77	0.21	0.66	0.29
	lumbar extension	1.40	3.88	6.04	0.33	0.31	1.68
	lumbar rotation	0.54	4.77	2.12	0.20	0.98	0.40
T2: Sit-to-stand	ankle l	1.56	2.50	3.24	0.51	0.40	1.29
	ankle r	1.66	12.04	5.39	0.65	1.03	1.32
	hip flexion l	4.71	8.60	10.06	1.01	2.71	2.62
	hip flexion r	4.66	9.24	10.28	1.00	2.53	2.60
	knee l	4.13	3.78	7.64	1.34	1.88	3.36
	knee r	4.33	3.34	8.60	1.51	1.28	3.40
	lumbar bending	1.16	2.49	1.45	0.56	0.54	0.33
	lumbar extension	2.93	3.91	4.08	1.11	1.44	1.18
	lumbar rotation	0.88	3.50	1.84	0.23	0.52	0.53
T3: Forward reach	arm adduction l	0.57	2.40	1.38	0.07	0.38	0.29
	arm adduction r	1.33	4.06	2.19	0.39	0.33	0.67
	arm flexion l	1.08	4.89	1.94	0.38	1.29	0.94
	arm flexion r	3.02	5.62	4.25	1.20	0.79	1.47
	arm rotation l	3.59	16.59	5.06	0.32	3.69	2.37
	arm rotation r	10.28	21.85	12.90	3.95	3.70	4.92
	elbow flexion l	1.85	4.16	1.74	0.63	0.83	0.24
	elbow flexion r	2.89	8.74	4.22	0.53	1.26	1.57
	lumbar bending	0.43	2.11	1.15	0.10	0.25	0.43
	lumbar extension	0.94	1.76	1.31	0.43	0.32	0.52
	lumbar rotation	0.79	6.08	1.19	0.19	0.44	0.40

Continued on next page

Table 4 – continued from previous page

Task	Selected variable	RMSE (°)			SD		
		C1	C2	C3	C1	C2	C3
T4: Overhead reach	arm adduction l	0.52	2.08	1.27	0.10	0.23	0.29
	arm adduction r	3.07	9.64	7.40	0.66	1.23	1.81
	arm flexion l	1.41	10.05	1.91	0.27	1.73	0.36
	arm flexion r	5.49	28.32	12.75	2.08	5.58	3.94
	arm rotation l	3.39	17.16	5.04	1.45	5.34	2.08
	arm rotation r	12.74	46.20	25.27	3.24	6.35	5.17
	elbow flexion l	1.80	10.52	3.21	0.78	2.14	0.97
	elbow flexion r	5.35	20.51	9.16	1.08	2.63	1.55
	lumbar bending	0.44	1.65	0.99	0.10	0.44	0.22
	lumbar extension	0.82	2.08	1.81	0.31	0.68	0.25
	lumbar rotation	1.24	5.28	2.02	0.26	0.76	0.33
T5: Object lifting	arm flexion l	3.38	7.68	9.96	1.22	1.22	1.76
	arm flexion r	3.38	11.00	9.67	1.04	1.58	1.91
	elbow flexion l	2.47	6.68	6.33	0.79	0.30	1.43
	elbow flexion r	2.51	9.83	6.53	0.81	1.72	1.55
	lumbar bending	2.15	12.95	6.68	0.78	0.67	1.13
	lumbar extension	2.65	9.10	5.37	0.81	0.85	1.46
	lumbar rotation	2.33	13.07	5.46	0.48	0.56	1.03
T6: Supine reach	arm adduction l	6.79	11.98	12.65	2.67	2.15	–
	arm adduction r	6.16	13.00	8.53	2.41	2.53	–
	arm flexion l	7.40	21.68	9.20	2.09	2.82	–
	arm flexion r	8.49	17.47	13.53	2.70	3.33	–
	elbow flexion l	9.26	14.84	11.27	3.24	3.05	–
	elbow flexion r	11.94	27.84	18.20	3.04	8.89	–
	lumbar bending	2.33	5.42	2.62	0.27	0.51	–
	lumbar extension	2.58	6.80	4.10	0.64	1.36	–
	lumbar rotation	6.69	11.29	4.10	2.56	2.00	–

Note. Values are reported in degrees. RMSE values were calculated relative to the mean trajectory of condition 1 (C1)

D. Welch's t-test (C2 vs C1) and (C3 vs C1)

Table 5. Welch's t-test results comparing C2 and C1. Row colours indicate significance difference ($p < 0.05$); True (green) and False (red)

Task	Selected variable	n		RMSE (°)			t	p
		C2	C1	Mean C2	Mean C1	Difference		
T1: Double squat	ankle l	6	7	3.09	1.40	1.69	2.71	.037
	ankle r	6	7	10.34	1.01	9.34	10.27	< .001
	hip flexion l	6	7	7.60	2.08	5.52	8.32	< .001
	hip flexion r	6	7	7.96	2.01	5.96	10.81	< .001
	knee_angle_l	6	7	4.39	2.54	1.85	3.99	.002
	knee_angle_r	6	7	3.14	2.72	0.42	0.80	.441
	lumbar_bending	6	7	2.84	0.52	2.32	8.24	< .001
	lumbar_extension	6	7	3.88	1.40	2.48	13.78	< .001
	lumbar_rotation	6	7	4.77	0.54	4.24	10.45	< .001
T2: Sit-to-stand	ankle l	7	7	2.50	1.56	0.94	3.82	.003
	ankle r	7	7	12.04	1.66	10.38	22.55	< .001
	hip flexion l	7	7	8.60	4.71	3.89	3.56	.008
	hip flexion r	7	7	9.24	4.66	4.58	4.45	.002
	knee_angle_l	7	7	3.78	4.13	-0.34	-0.39	.701
	knee_angle_r	7	7	3.34	4.33	-0.98	-1.32	.212
	lumbar_bending	7	7	2.49	1.16	1.34	4.56	< .001
	lumbar_extension	7	7	3.91	2.93	0.98	1.43	.181
	lumbar_rotation	7	7	3.50	0.88	2.62	12.23	< .001
T3: Forward reach	arm_add_l	6	6	2.40	0.57	1.82	11.42	< .001
	arm_add_r	6	6	4.06	1.33	2.73	12.97	< .001
	arm_flex_l	6	6	4.89	1.08	3.81	6.95	< .001
	arm_flex_r	6	6	5.62	3.02	2.61	4.46	.002
	arm_rot_l	6	6	16.59	3.59	13.00	8.60	< .001
	arm_rot_r	6	6	21.85	10.28	11.57	5.23	< .001
	elbow_flex_l	6	6	4.16	1.85	2.32	5.45	< .001
	elbow_flex_r	6	6	8.74	2.89	5.85	10.44	< .001
	lumbar_bending	6	6	2.11	0.43	1.68	15.44	< .001
	lumbar_extension	6	6	1.76	0.94	0.82	3.75	.004
	lumbar_rotation	6	6	6.08	0.79	5.29	26.71	< .001

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Table 5 – continued from previous page

Task	Selected variable	*n*		RMSE (°)			*t*	*p*
		C2	C1	Mean C2	Mean C1	Difference		
T4: Overhead reach	arm_add_l	5	6	2.08	0.52	1.56	14.04	< .001
	arm_add_r	5	6	9.64	3.07	6.57	10.70	< .001
	arm_flex_l	5	6	10.05	1.41	8.64	11.07	< .001
	arm_flex_r	5	6	28.32	5.49	22.83	8.66	< .001
	arm_rot_l	5	6	17.16	3.39	13.77	5.59	.004
	arm_rot_r	5	6	46.20	12.74	33.46	10.68	< .001
	elbow_flex_l	5	6	10.52	1.80	8.72	8.66	< .001
	elbow_flex_r	5	6	20.51	5.35	15.16	12.08	< .001
	lumbar_bending	5	6	1.65	0.44	1.21	6.01	.003
	lumbar_extension	5	6	2.08	0.82	1.26	3.85	.010
	lumbar_rotation	5	6	5.28	1.24	4.04	11.32	< .001
T5: Object lifting	arm_flex_l	6	6	7.68	3.38	4.30	6.09	< .001
	arm_flex_r	6	6	11.00	3.38	7.62	9.85	< .001
	elbow_flex_l	6	6	6.68	2.47	4.20	12.17	< .001
	elbow_flex_r	6	6	9.83	2.51	7.33	9.42	< .001
	lumbar_bending	6	6	12.95	2.15	10.81	25.77	< .001
	lumbar_extension	6	6	9.10	2.65	6.44	13.42	< .001
	lumbar_rotation	6	6	13.07	2.33	10.74	35.77	< .001
T6: Supine reach	arm_add_l	5	3	11.98	6.79	5.19	2.86	.053
	arm_add_r	5	3	13.00	6.16	6.83	3.81	.015
	arm_flex_l	5	3	21.68	7.40	14.28	8.19	< .001
	arm_flex_r	5	3	17.47	8.49	8.98	4.17	.008
	elbow_flex_l	5	3	14.84	9.26	5.58	2.41	.072
	elbow_flex_r	5	3	27.84	11.94	15.90	3.66	.013
	lumbar_bending	5	3	5.42	2.33	3.10	11.22	< .001
	lumbar_extension	5	3	6.80	2.58	4.22	5.94	.001
	lumbar_rotation	5	3	11.29	6.69	4.59	2.66	.065

Table 6. Welch's t-test results comparing C3 and C1. Row colours indicate significance difference ($p < 0.05$); True (green) and False (red)

Task	Selected variable	n		RMSE (°)			t	p
		C3	C1	Mean C3	Mean C1	Difference		
T1: Double squat	ankle l	7	7	3.41	1.40	2.00	4.37	.003
	ankle r	7	7	3.37	1.01	2.36	11.95	< .001
	hip flexion l	7	7	6.91	2.08	4.83	6.77	< .001
	hip flexion r	7	7	6.51	2.01	4.51	6.07	< .001
	knee angle l	7	7	7.24	2.54	4.70	6.00	< .001
	knee angle r	7	7	7.85	2.72	5.13	8.37	< .001
	lumbar bending	7	7	1.77	0.52	1.24	9.23	< .001
	lumbar extension	7	7	6.04	1.40	4.64	7.15	< .001
	lumbar rotation	7	7	2.12	0.54	1.58	9.38	< .001
T2: Sit-to-stand	ankle l	7	7	3.24	1.56	1.68	3.19	.013
	ankle r	7	7	5.39	1.66	3.72	6.68	< .001
	hip flexion l	7	7	10.06	4.71	5.35	5.03	.001
	hip flexion r	7	7	10.28	4.66	5.62	5.34	< .001
	knee angle l	7	7	7.64	4.13	3.51	2.57	.034
	knee angle r	7	7	8.60	4.33	4.28	3.04	.015
	lumbar bending	7	7	1.45	1.16	0.29	1.20	.259
	lumbar extension	7	7	4.08	2.93	1.15	1.87	.086
	lumbar rotation	7	7	1.84	0.88	0.96	4.35	.002
T3: Forward reach	arm adduction l	6	6	1.38	0.57	0.81	6.69	< .001
	arm adduction r	6	6	2.19	1.33	0.86	2.71	.026
	arm flexion l	6	6	1.94	1.08	0.86	2.09	.078
	arm flexion r	6	6	4.25	3.02	1.23	1.60	.143
	arm rotation l	6	6	5.06	3.59	1.48	1.52	.188
	arm rotation r	6	6	12.90	10.28	2.62	1.02	.333
	elbow flexion l	6	6	1.74	1.85	-0.10	-0.38	.715
	elbow flexion r	6	6	4.22	2.89	1.33	1.96	.096
	lumbar bending	6	6	1.15	0.43	0.72	3.97	.009
	lumbar extension	6	6	1.31	0.94	0.37	1.35	.209
	lumbar rotation	6	6	1.19	0.79	0.40	2.16	.066

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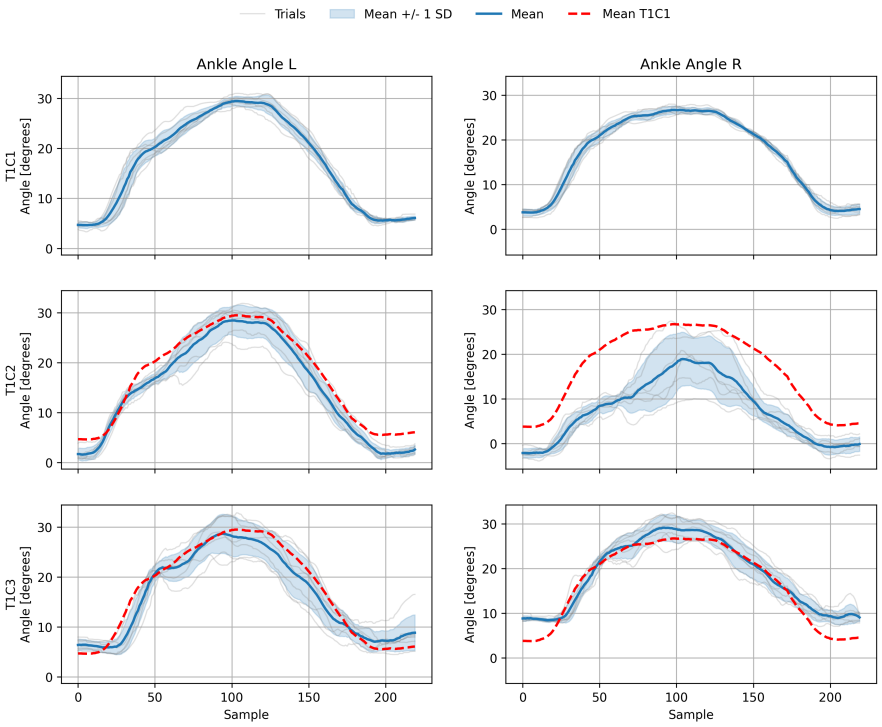
Table 6 – continued from previous page

Task	Selected variable	*n*		RMSE (°)			*t*	*p*
		C3	C1	Mean C3	Mean C1	Difference		
T4: Overhead reach	arm adduction l	5	6	1.27	0.52	0.75	5.57	.003
	arm adduction r	5	6	7.40	3.07	4.33	5.07	.004
	arm flexion l	5	6	1.91	1.41	0.50	2.57	.035
	arm flexion r	5	6	12.75	5.49	7.26	3.71	.011
	arm rotation l	5	6	5.04	3.39	1.65	1.50	.177
	arm rotation r	5	6	25.27	12.74	12.53	4.70	.003
	elbow flexion l	5	6	3.21	1.80	1.41	2.63	.031
	elbow flexion r	5	6	9.16	5.35	3.81	4.62	.002
	lumbar bending	5	6	0.99	0.44	0.54	5.20	.003
	lumbar extension	5	6	1.81	0.82	0.99	5.91	< .001
	lumbar rotation	5	6	2.02	1.24	0.79	4.28	.003
T5: Object lifting	arm flexion l	6	6	9.96	3.38	6.58	7.54	< .001
	arm flexion r	6	6	9.67	3.38	6.29	7.08	< .001
	elbow flexion l	6	6	6.33	2.47	3.85	5.77	< .001
	elbow flexion r	6	6	6.53	2.51	4.02	5.64	< .001
	lumbar bending	6	6	6.68	2.15	4.53	8.08	< .001
	lumbar extension	6	6	5.37	2.65	2.72	3.99	.004
	lumbar rotation	6	6	5.46	2.33	3.13	6.73	< .001
T6: Supine reach	arm adduction l	1	3	12.65	6.79	5.86	–	–
	arm adduction r	1	3	8.53	6.16	2.37	–	–
	arm flexion l	1	3	9.20	7.40	1.80	–	–
	arm flexion r	1	3	13.53	8.49	5.04	–	–
	elbow flexion l	1	3	11.27	9.26	2.01	–	–
	elbow flexion r	1	3	18.20	11.94	6.26	–	–
	lumbar bending	1	3	2.62	2.33	0.29	–	–
	lumbar extension	1	3	4.10	2.58	1.52	–	–
	lumbar rotation	1	3	4.10	6.69	-2.59	–	–

Note. There is no test possible for Task 6 because there is just one succesfull trial in C3

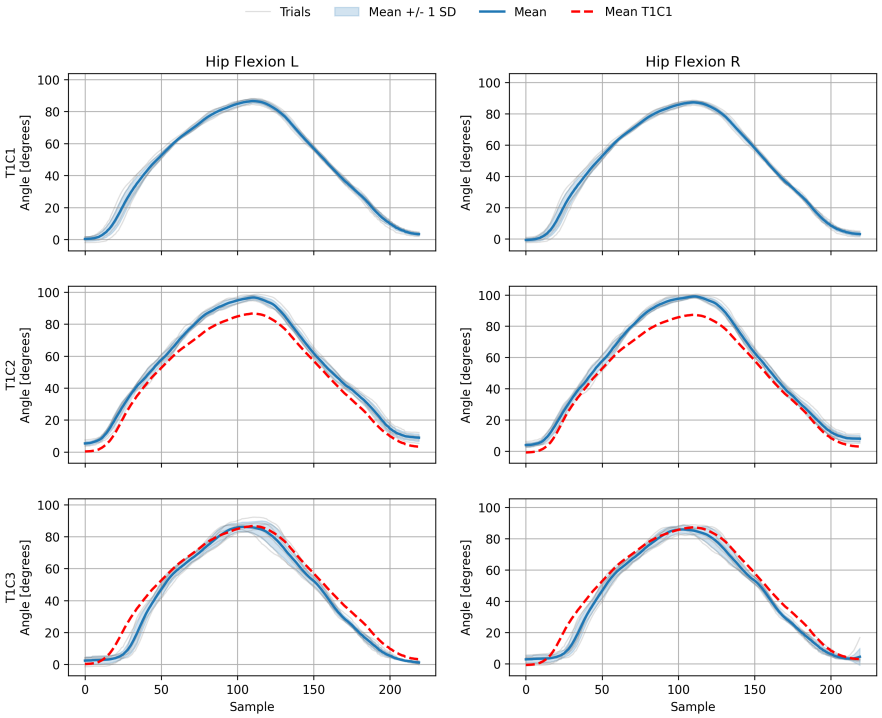
E. Individual trial data

All trials are represented in these figures per variable and per task. Within each figure and panel, the top, middle, and bottom rows represent C1, C2, and C3, respectively. Light-grey lines represent individual successful trials, the solid blue line represents the mean trajectory, and the shaded band represents ±1 SD. The dashed red line represents the mean trajectory of C1.

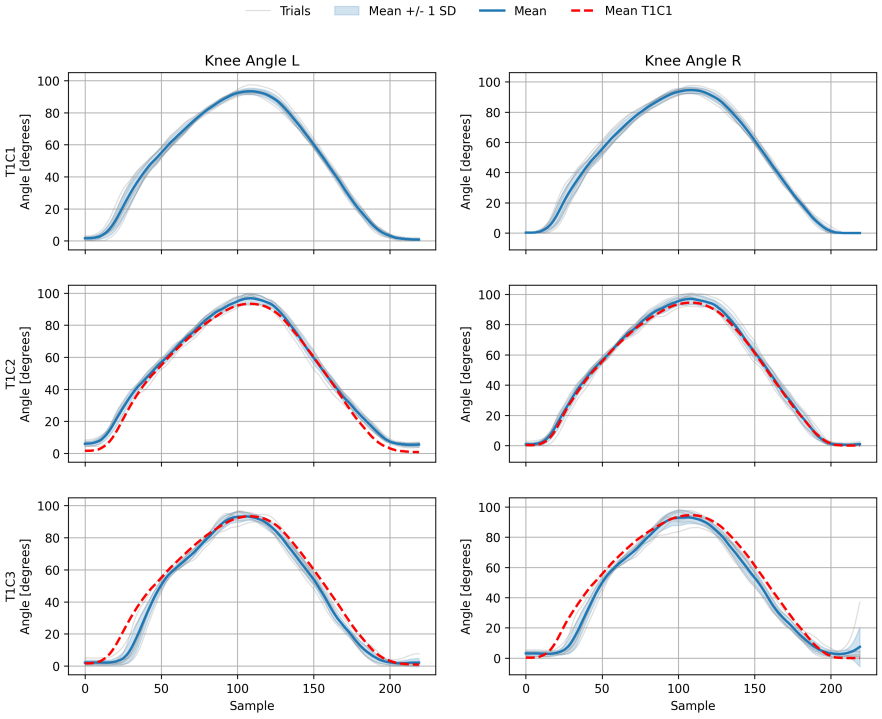


(a) T1: Ankle

Figure 5. Task 1: Squat

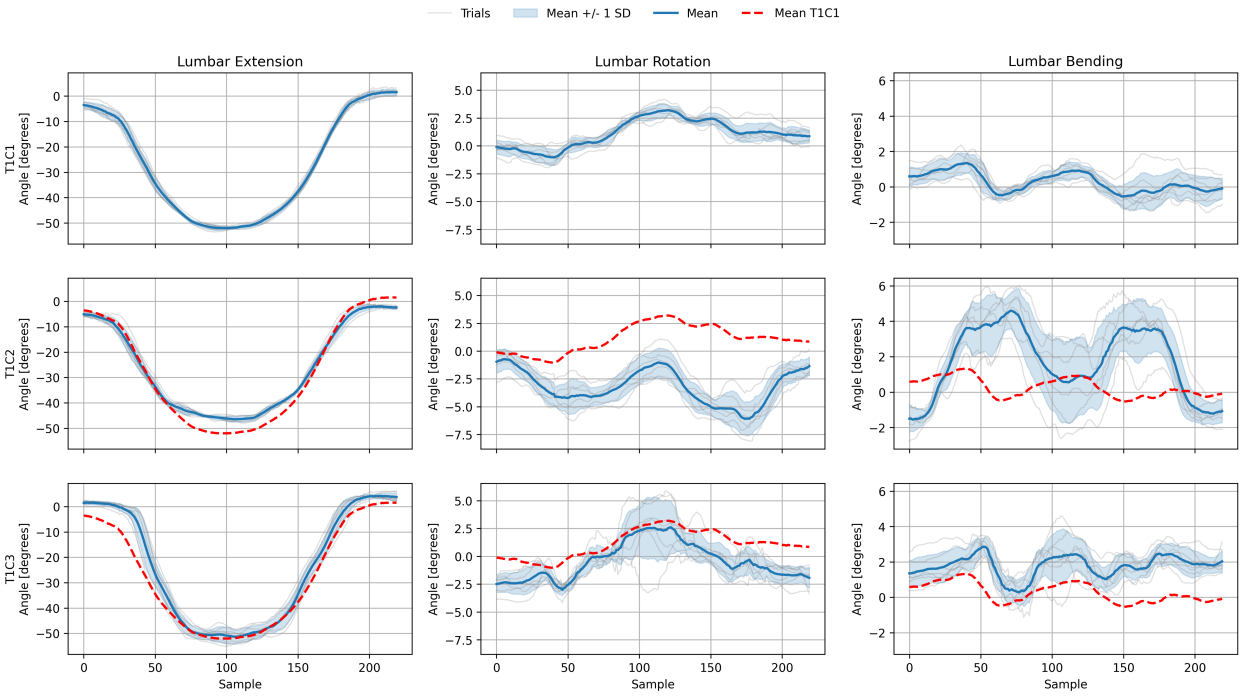


(b) T1: Hip flexion



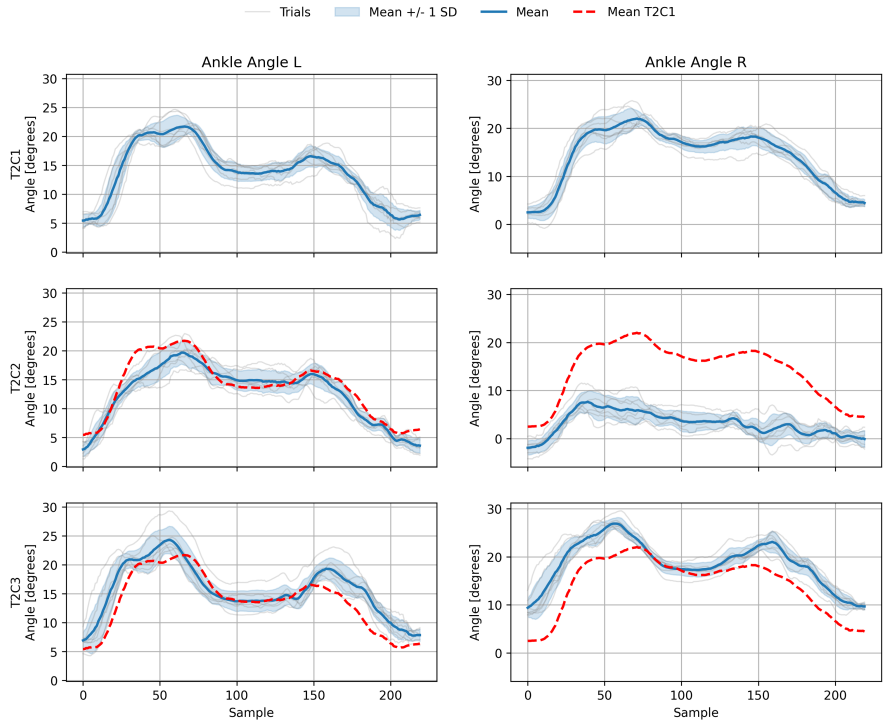
(c) T1: Knee flexion

Figure 5. (continued)



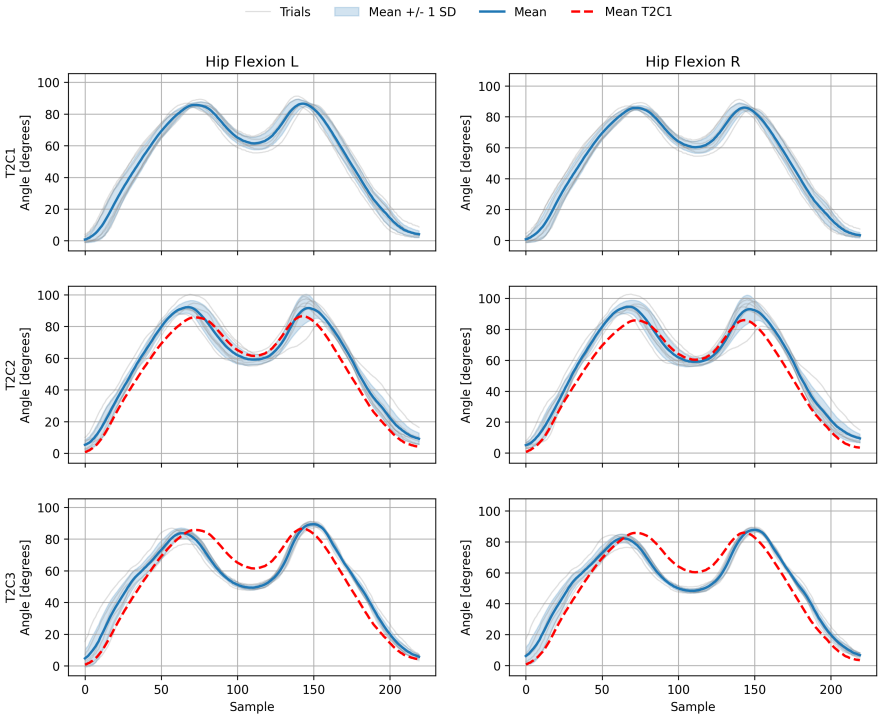
(d) T1: Lumbar angles

Figure 5. (continued)

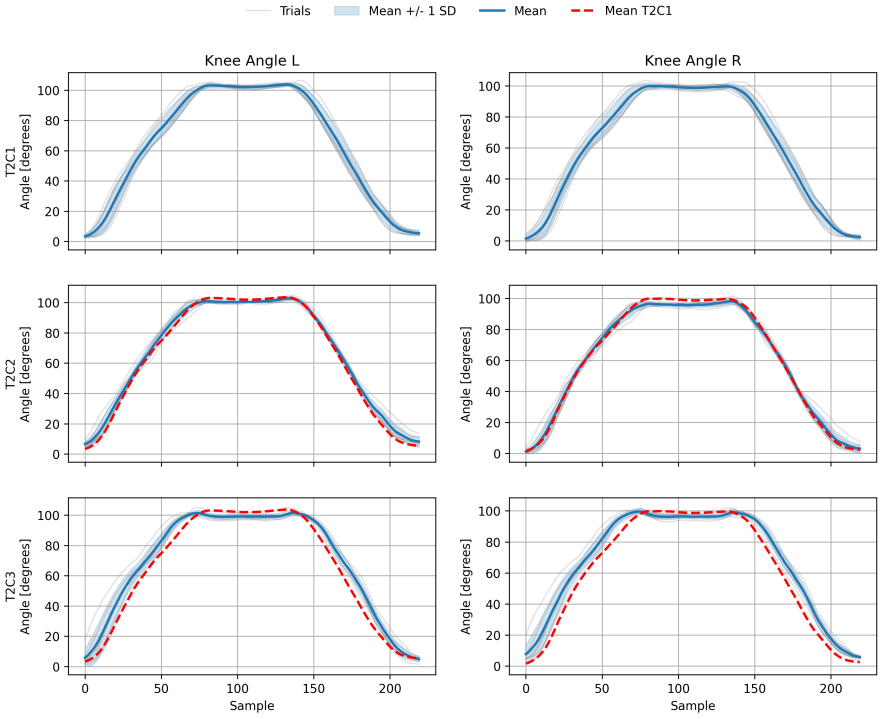


(a) T2: Ankle angle

Figure 6. Task 2: sit-to-stand

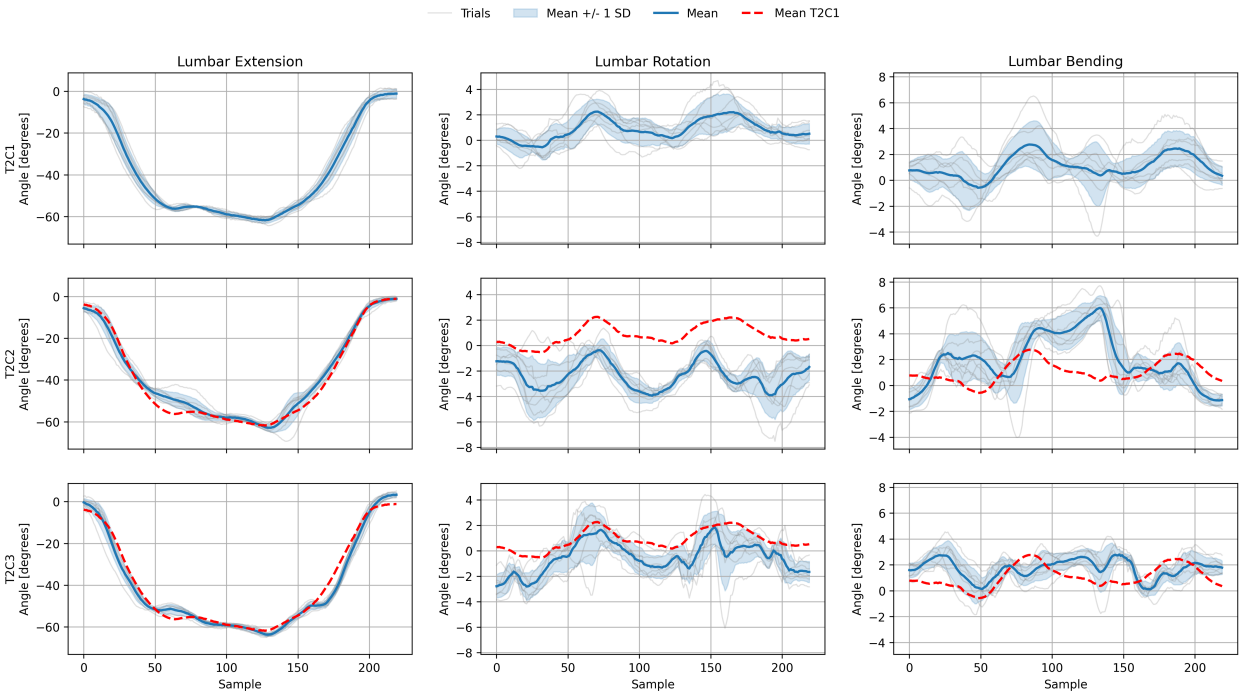


(b) T2: Hip flexion



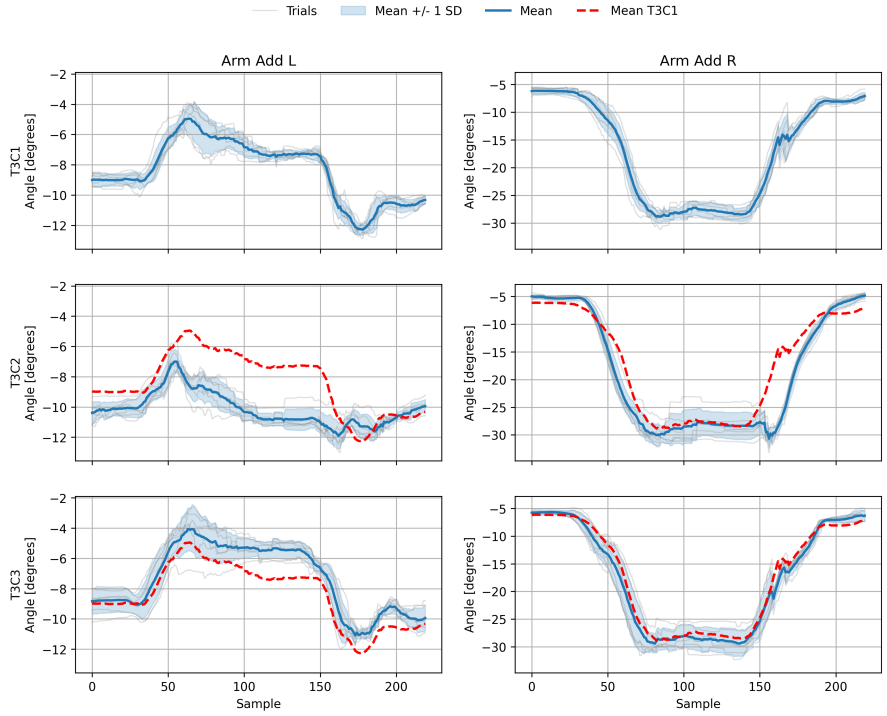
(c) T2: Knee flexion

Figure 6. (continued)



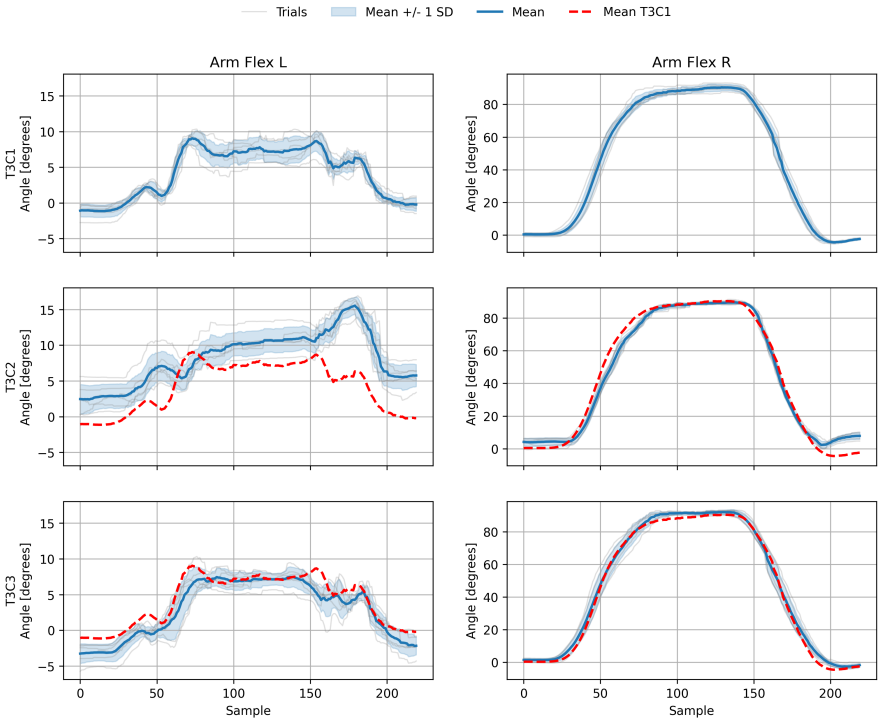
(d) T2: Lumbar angles

Figure 6. (continued)

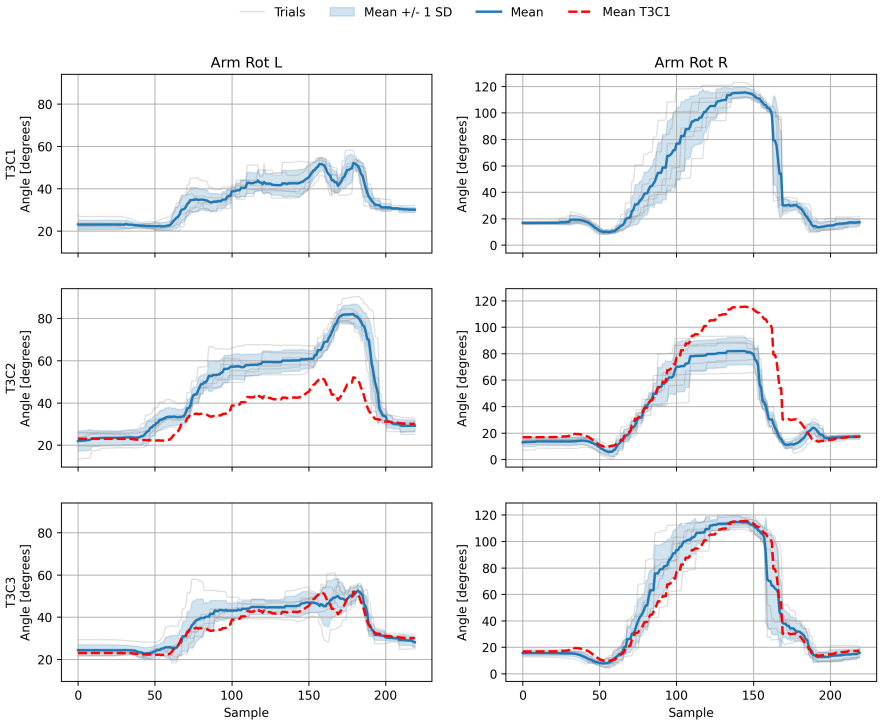


(a) T3: Arm adduction

Figure 7. Task 3: Forward reach

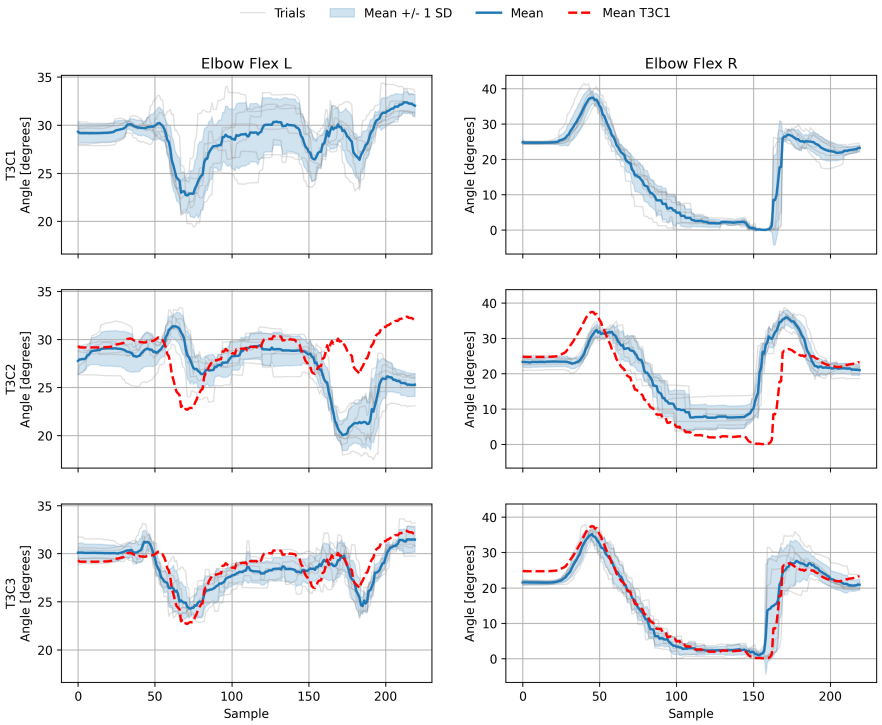


(b) T3: Arm flexion

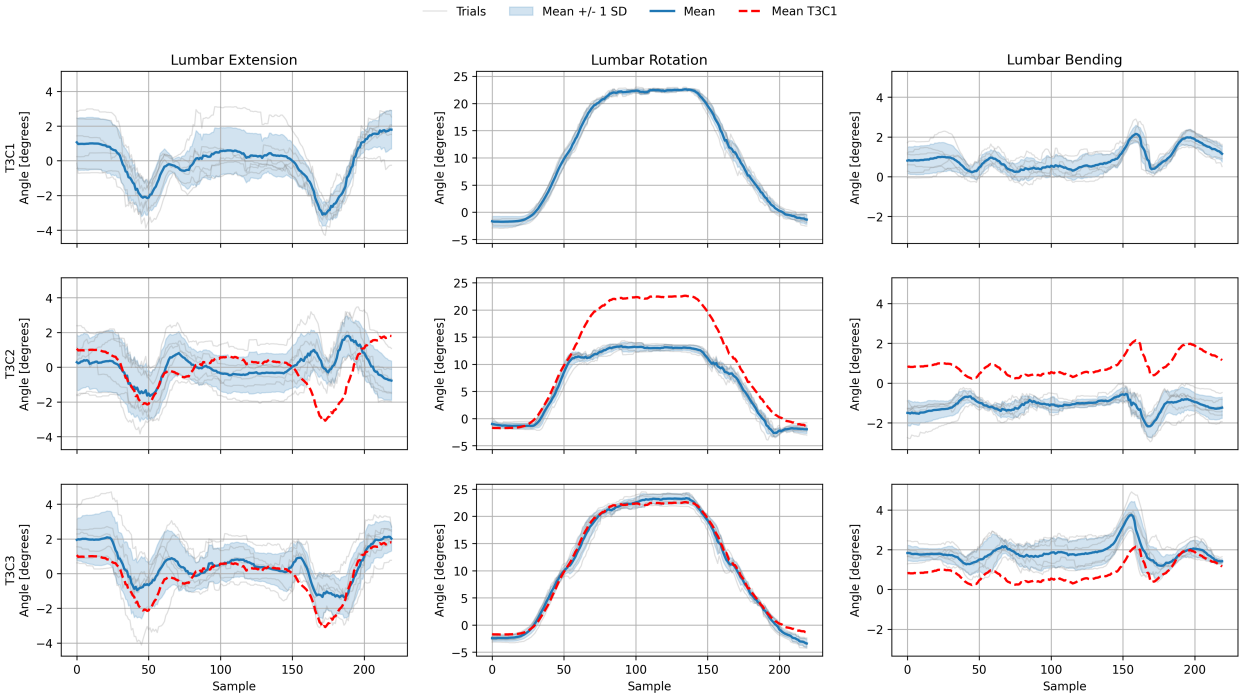


(c) T3: Arm rotation

Figure 7. (continued)

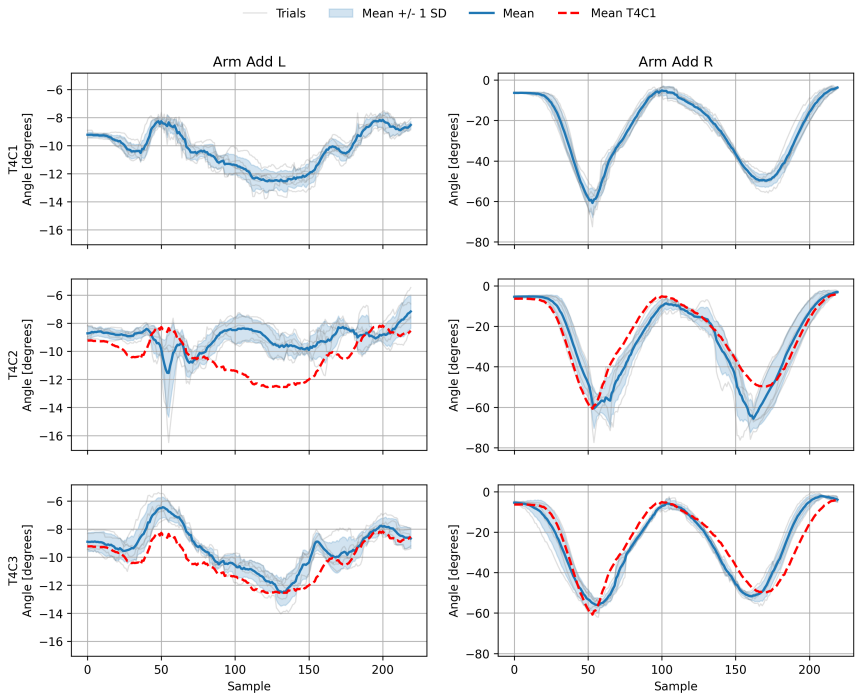


(d) T3: Elbow flexion

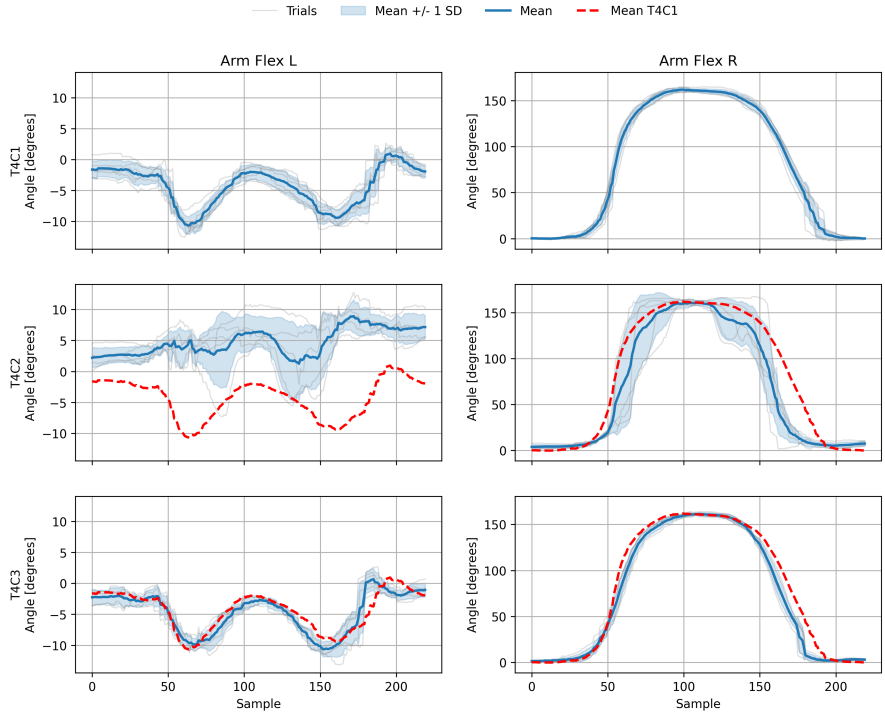


(e) T3: Lumbar angles

Figure 7. (continued)

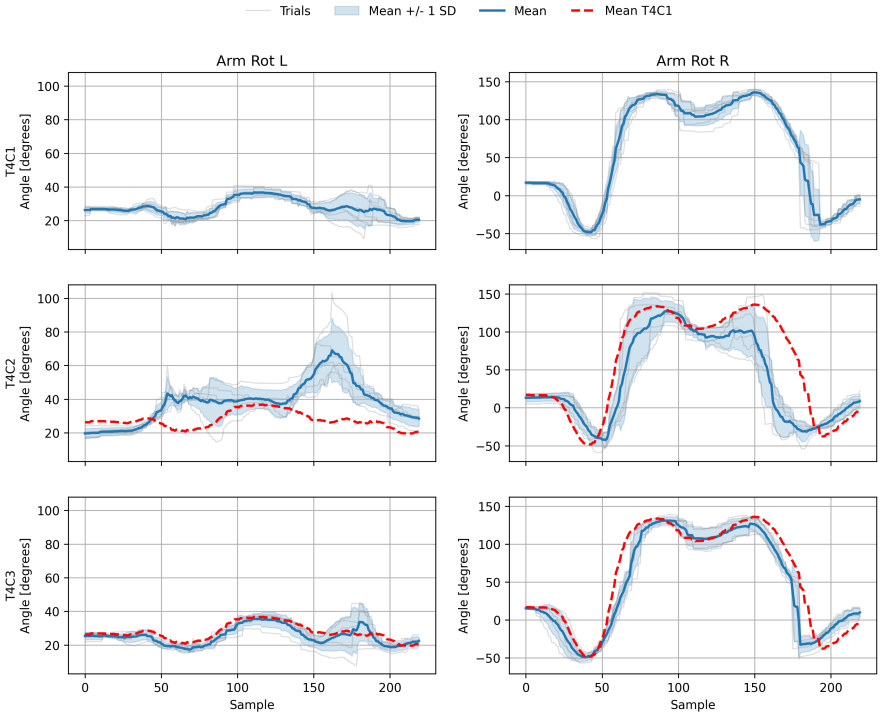


(a) T4: Arm adduction

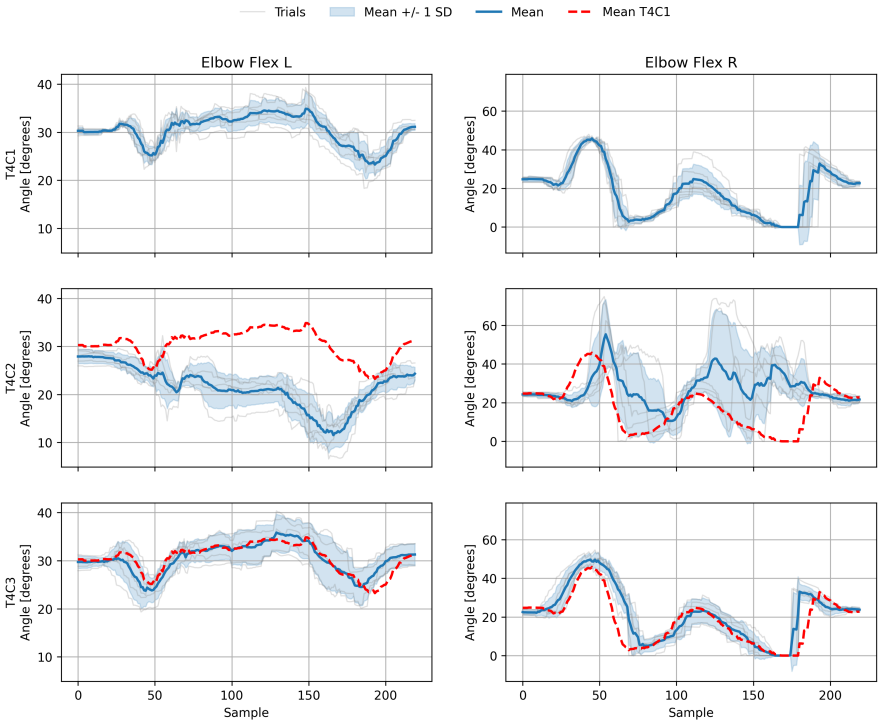


(b) T4: Arm flexion

Figure 8. Task 4: Overhead reach

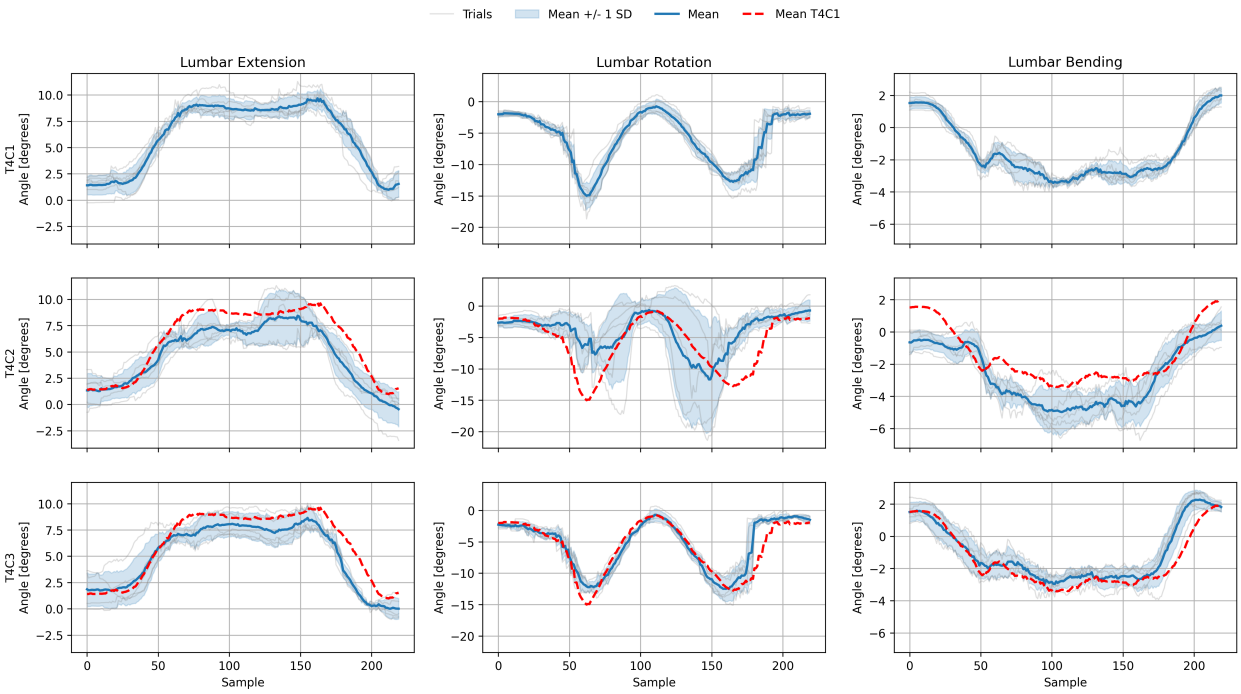


(c) T4: Arm rotation



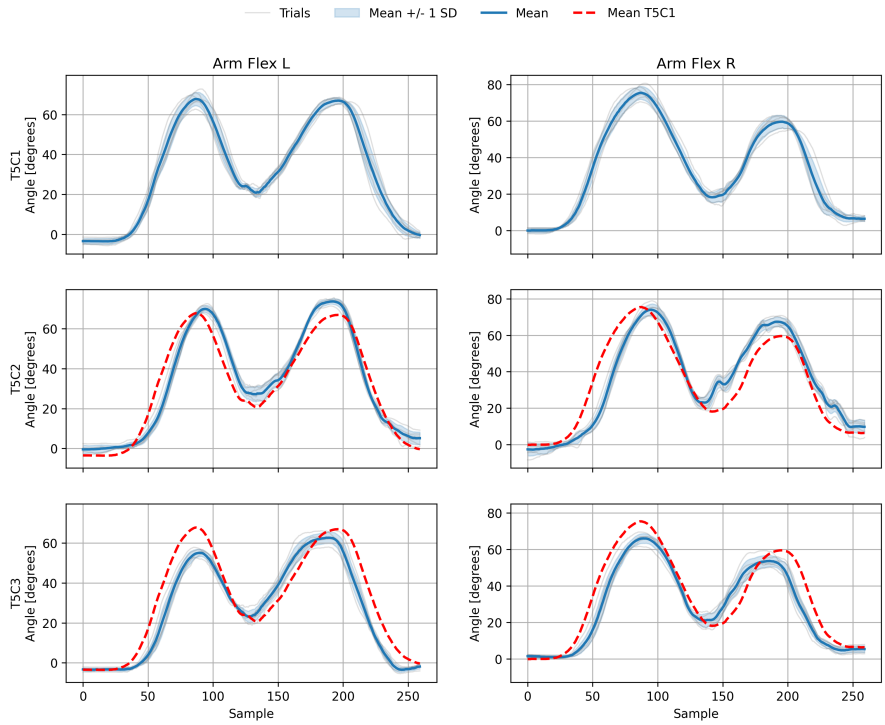
(d) T4: Elbow flexion

Figure 8. (continued)



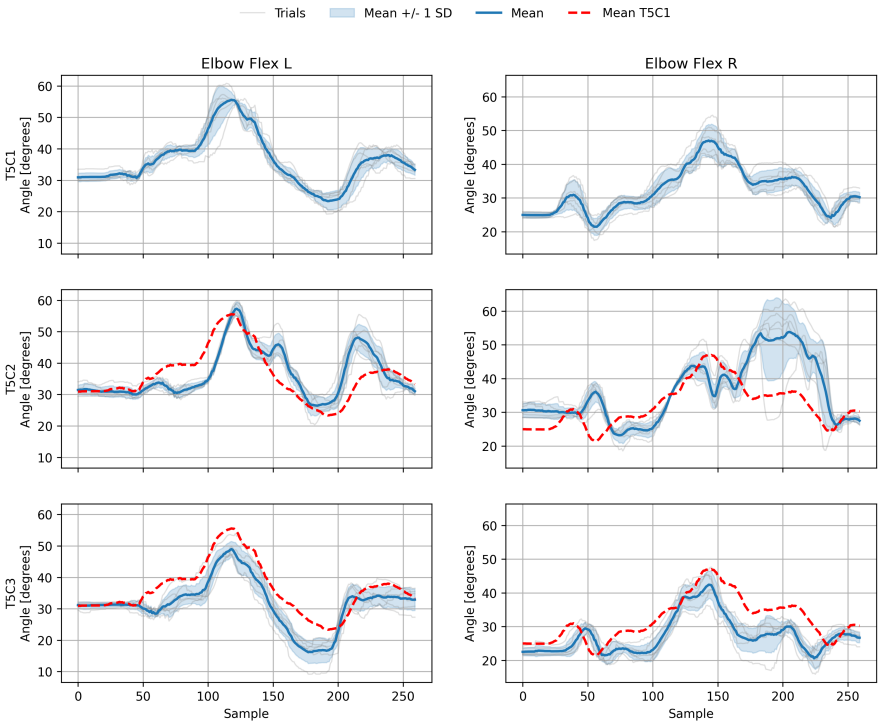
(e) T4: Lumbar angles

Figure 8. (continued)

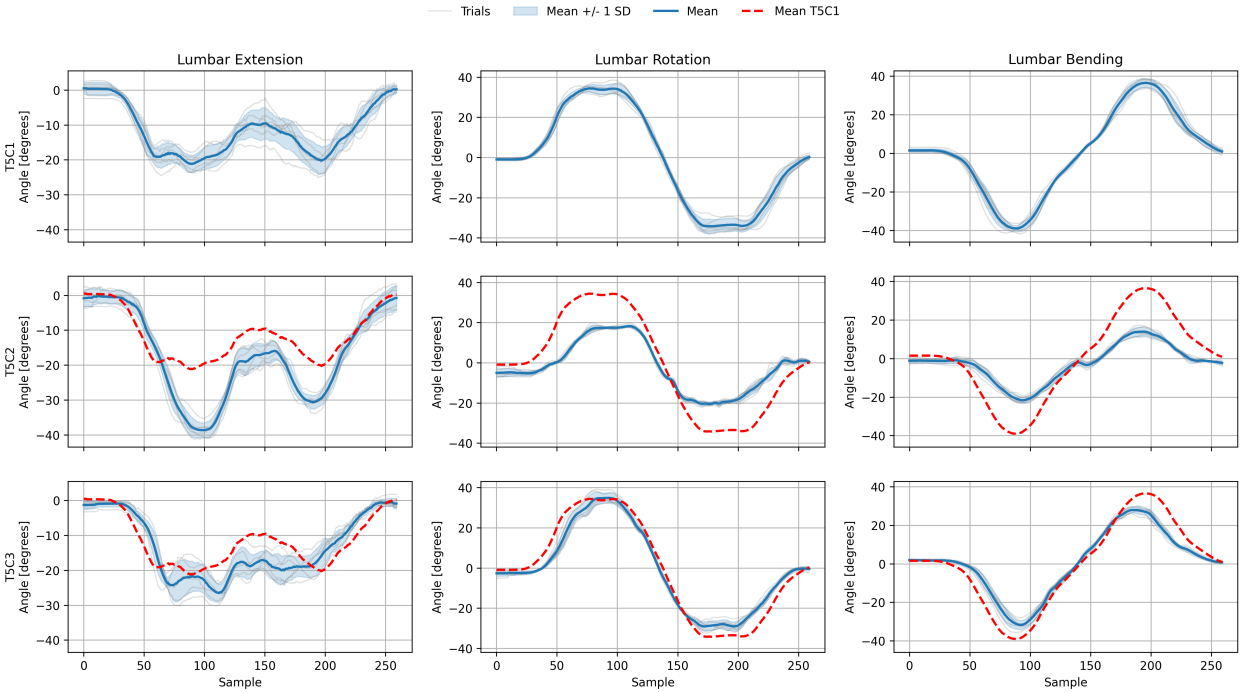


(a) T5: Arm flexion

Figure 9. Task 5: Object Lifting

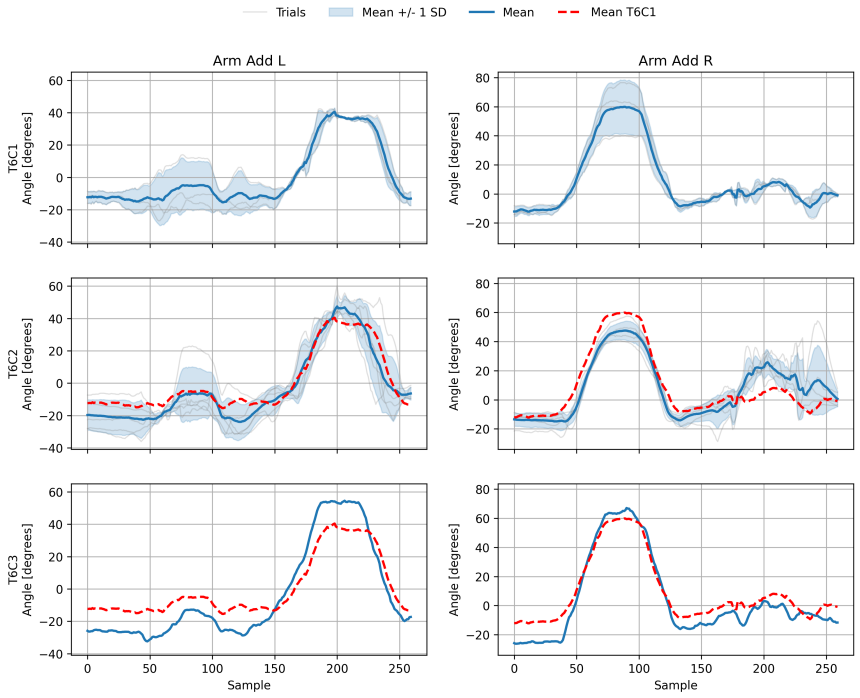


(b) T5: Elbow flexion

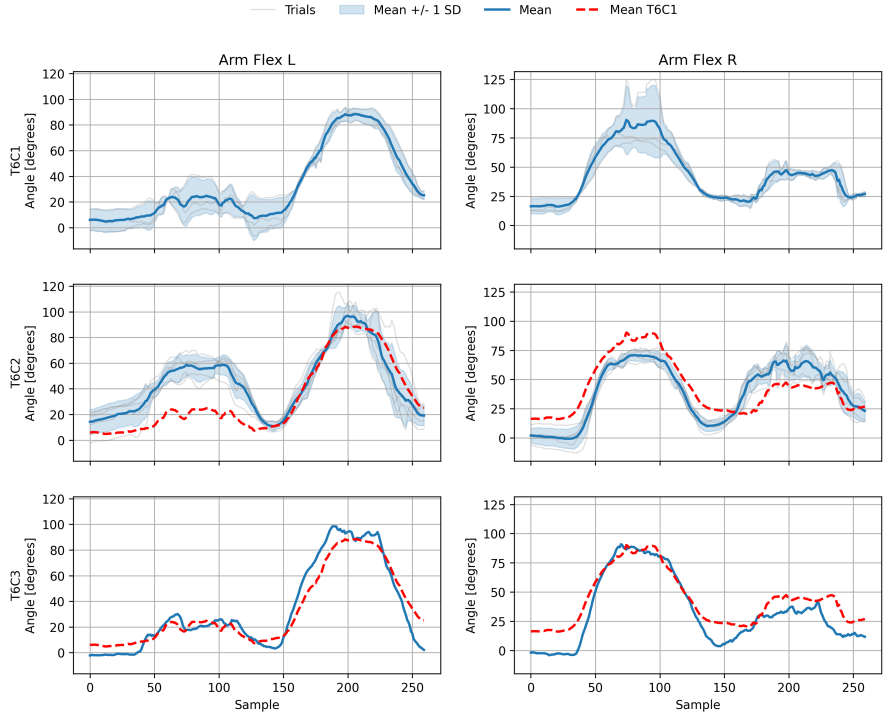


(c) T5: Lumbar angles

Figure 9. (continued)

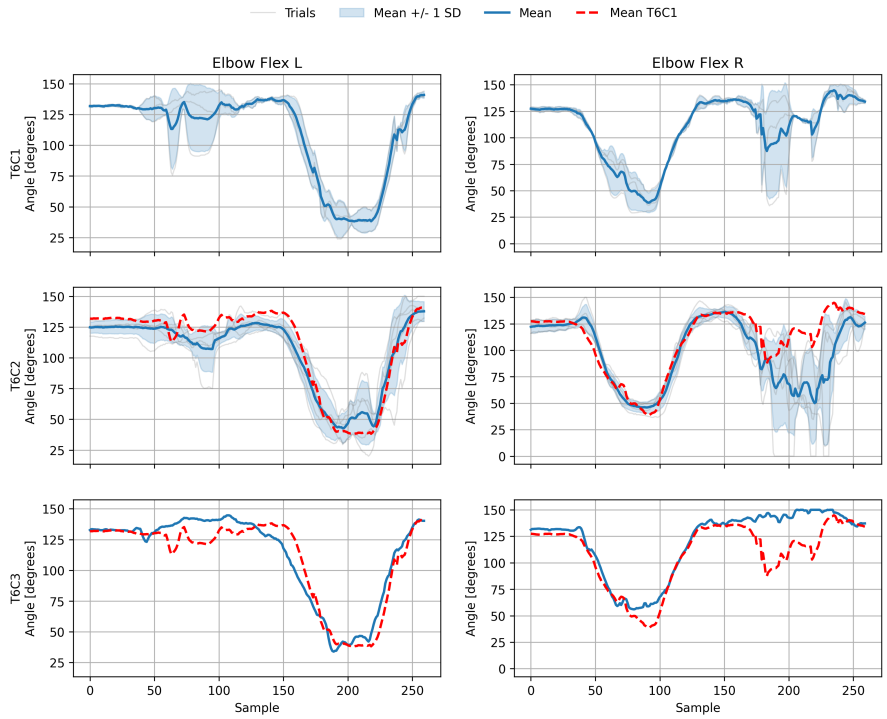


(a) T6: Arm adduction

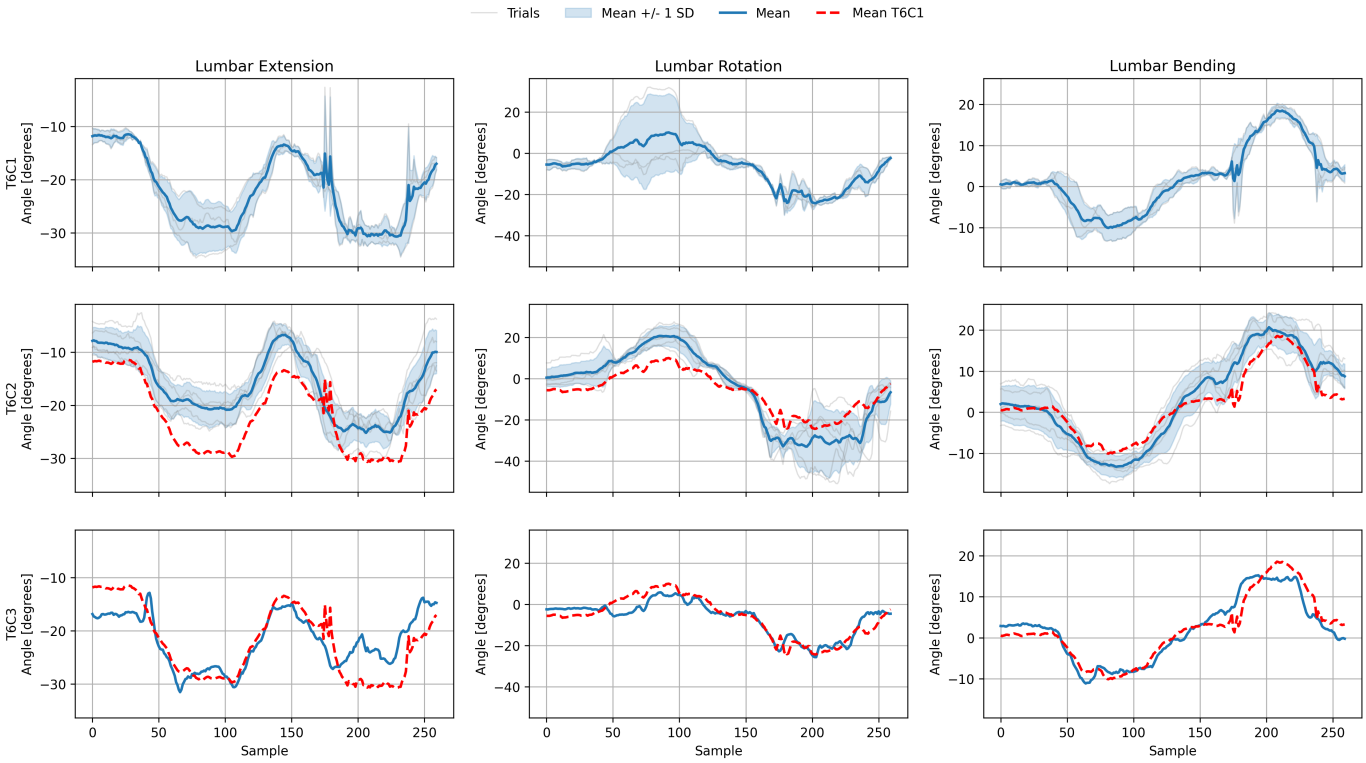


(b) T6: Arm flexion

Figure 10. Task 6: Supine reach



(c) T6: Elbow flexion



(d) T6: Lumbar angles

Figure 10. (continued)