

Detecting fatigue in sit-to-stand transitions using knee flexion and dynamic time warping

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Abstract:

The sit-to-stand (STS) transition, a fundamental movement in daily life, is commonly used to assess strength, balance, and fall risk in older adults. Analyzing spinal kinematics during STS can provide valuable insights into physical health, particularly in individuals with spinal disorders or post-stroke. However, traditional methods for measuring these kinematics often involve expensive equipment and invasive procedures. This study, proposes a novel method for detecting fatigue in STS movements using video-based pose estimation without the need for attached sensors, focusing on knee flexion patterns and using dynamic time warping analysis. We used PoseNet to extract knee joints and analyzed knee angles using Dynamic Time Warping (DTW) to evaluate the consistency of movement before and after exercise. The results showed that Subject 5 had the lowest DTW value, reflecting more consistent and stable movement after exercise. In contrast, Subject 1 showed a significant difference with the highest DTW value, possibly due to fatigue. The results illustrated that the movement trajectory in the pre-exercise condition showed a smooth and controlled movement during the transition from sitting to standing. Meanwhile, in the post-exercise condition, there is a significant deviation in the knee trajectory, especially during the upward phase (standing). Observation of knee and hip trajectories in all subjects showed increased movement variability, especially in the knee after exercise, indicating that fatigue affects knee control more than the hip. This method successfully provided significant results regarding fatigue-related biomechanical changes without using expensive sensors. However, further research with a larger and more diverse number of subjects is needed.

Key Words: Sit-To-Stand Transition, fatigue detection, pose detection, body landmark tracking, dynamic time warping

Introduction

Sit-to-stand (STS) is a common activity in daily life that involves coordinated movements of various joints, including the spine, neck, and hips (trunk). The STS assessment evaluates a person's ability to transition from sitting to standing and is primarily used to assess strength, balance, and fall risk in older adults. Inadequate coordination of joint movements during the STS transition can serve as an important indicator of an individual's physical health (Melo et al., 2022; Roldán Jiménez et al., 2019). However, individuals with specific health conditions, such as spinal cord injuries or those recovering from a stroke, may find this movement challenging (Waiteman et al., 2022; Schwarz et al., 2022). Therefore, monitoring the kinematic characteristics of the spine during the STS process is essential for developing effective interventions aimed at enhancing STS performance in those with spinal disorders.

The primary challenge in STS assessment is the difficulty in accurately and objectively measuring spinal kinematics (Inoue & Matsuo, 2020), which often require specialized, costly instrumentation (Atrsaie et al., 2022). Additionally, spinal kinematic measurements can be affected by factors such as age, gender, and the individual's physical condition (Nioti et al., 2022; Izzo et al., 2023). Therefore, there is a need for an accurate, objective, and non-invasive method to measure spinal kinematics during STS movements using cost-effective and user-friendly technology. Generally, STS assessment can be performed using sensors or computer vision techniques (Dang et al., 2020). For sensor-based assessments, an inertial measuring unit (IMU) or pressure sensor can be used. Conversely, computer vision-based assessments can use either markers or marker less techniques. This study specifically focuses on the computer vision-based STS assessment method.

Previous studies have used Red-Green-Blue-Depth (RGB-D) cameras for video acquisition in STS assessments (Acorn et al., 2015; Röhling et al., 2022; Zhao et al., 2019). However, a limitation of this method is its dependence on indoor environments and sensitivity to lighting conditions. Additionally, some researchers have used markers to identify joints (Banerjee et al., 2014; Tulipani et al., 2022; Park et al., 2021), but this approach requires a time-intensive process to position the markers accurately. Other studies have explored the use of IMUs (Fudickar et al., 2020; Hanawa et al., 2019; Buraschi et al., 2022; Erfianto & Rizal, 2022) or

electromyogram (EMG) signals (Wang et al., 2022; Hsu et al., 2019; Abd Aziz et al., 2020) for data collection, yet these devices can still lack practicality for performing STS assessments.

Pose estimation is a method that can be effectively used for STS assessments. This technique estimates body joints using a computer program, eliminating the need for external devices to be attached to the subject. Pose estimation has already found extensive applications in areas such as augmented reality, robotics, and human motion recognition. To create a system for analyzing trunk movements during STS transitions, it would be beneficial to compare various effective pose estimation methods, including OpenPose (Washabaugh et al., 2022; Marusic et al., 2023), AlphaPose (Connie et al., 2022; Mundt et al., 2022), and MediaPipe (Siddiqui et al., 2023). Using pose estimation can lead to lower costs while providing more complete features.

This research introduces a method for detecting fatigue in STS movements through pose estimation. The results of pose estimation will be used to assess changes in knee angles. Data is captured using a camera, and key joints are extracted via MediaPipe. Knee flexion is determined by calculating the angles between the knee, hip, and ankle. Additionally, dynamic time warping (DTW) is used to evaluate the consistency of angular changes. The proposed method is expected to have applications in various cases involving biomechanical signal processing.

Material & methods

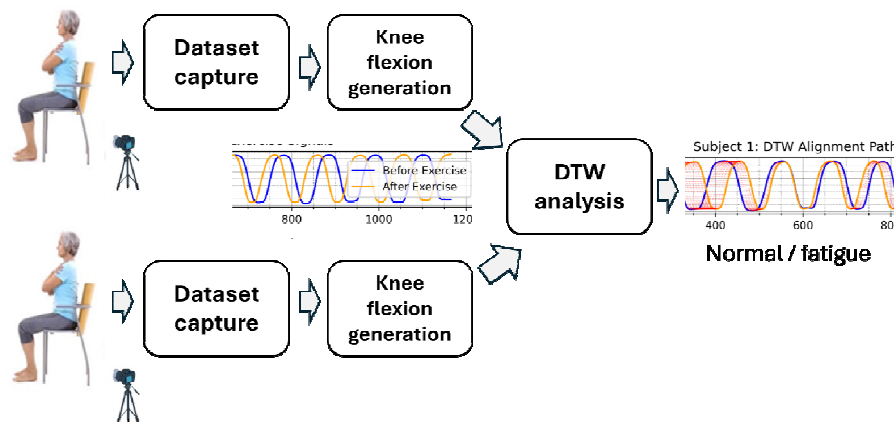


Fig. 1. Proposed system for fatigue detection on STS

The proposed system is shown in Figure 1. The subject completes ten repetitions of STS movements both before and after exercise. In this study, STS activity was assessed using pose estimation techniques. Pose estimation is a computer vision approach that detects and tracks human body positions in images and videos (Connie et al., 2022). This method uses convolutional neural networks (CNN) and recurrent neural networks (RNNs) to identify key points, such as joints, and to create a mathematical representation of human posture (Dubey & Dixit, 2023).

The displacement of the key joints—knee, hip, and foot—was measured to assess the knee angle. The changes in knee angle during the STS movement, both before and after exercise, were analyzed using the DTW method (Belkhouja et al., 2023). The displacement angle and the results of the DTW analysis served as the foundation for evaluating the subject's condition. Figure 2 shows the process of changing the knee angle during the transition from sitting to standing. Further details of each step are provided in the following subsection.

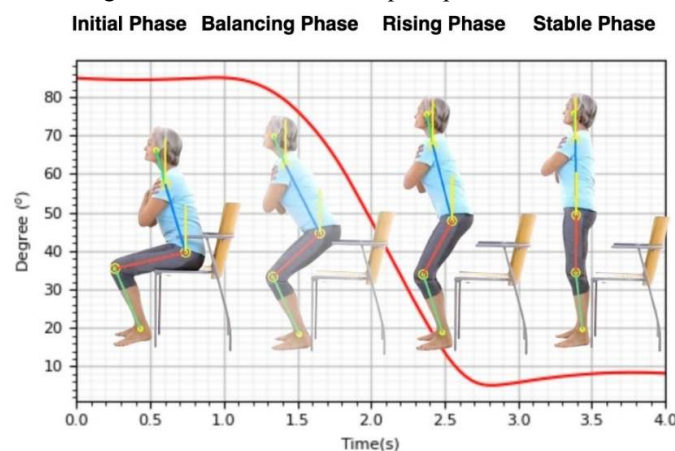


Fig. 2. Knee angle flexion to extension

Dataset

Data was collected from five subjects who completed ten repetitions of sit-to-stand movements. This movement was performed twice: once before and once after the exercise. The squat movement was performed 20 times, placing pressure on the subjects' knees to induce fatigue. After reviewing the experimental procedures presented to each participant, informed consent was obtained. By signing the attendance register, participants confirmed their agreement to participate in the study.



Fig. 3. Landmark Movement along STS pose

Knee Flexion

In a 2D video or image sequence, a pose estimation system predicts the relative coordinates of body landmark points. A projection model is generally used to convert these into 3D coordinates, representing real-world space. This model connects the 2D image coordinates to the 3D environment by including an estimate of depth. For a camera with a focal length f and pixel coordinates corresponding to image coordinates (x_i, y_i) , the transformation to real-world coordinates, where Z_i represents the depth or distance from the camera, can be modeled as follows:

$$X_i = \frac{(u_i - c_x) \cdot Z_i}{f_x}, \quad Y_i = \frac{(v_i - c_y) \cdot Z_i}{f_y} \quad (1)$$

where f_x and f_y are the camera's focal lengths in the x and y directions, respectively, c_x and c_y are the coordinates of the camera's principal point (optical center), and Z_i is the depth (distance from the camera). This depth is a vital parameter that can be estimated using advanced techniques such as machine learning or other vision methods.

This projection model transforms 2D image points into their corresponding 3D space points by estimating the depth Z_i . Once the 3D coordinates of key points—such as the hip, knee, and ankle—are determined, vectors between these joints can be calculated to analyze the joint angles. For instance, the vector from the hip to the knee is defined as follows:

$$\overrightarrow{HK} = (x_K - x_H, y_K - y_H, z_K - z_H) \quad (2)$$

The vector $\overrightarrow{HK}$ represents the relative position of the knee in relation to the hip in 3D space. Similar vectors can be created for other joints, such as the knee to the ankle. After calculating the vectors between joints, biomechanical analysis can proceed by measuring the angles formed between these vectors. The cosine of the angle between two vectors $\vec{A}$ and $\vec{B}$ is given by:

$$\cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{|\vec{A}| \cdot |\vec{B}|} \quad (3)$$

Where $\vec{A} \cdot \vec{B}$: dot product of vectors, while $|\vec{A}|$ and $|\vec{B}|$ are vector magnitude.

To calculate the knee angle, we need to determine the knee, hips, and ankle references as follows:

- Hips: $L_H = (x_H, y_H, z_H)$
- Knee: $L_K = (x_K, y_K, z_K)$
- Ankle: $L_A = (x_A, y_A, z_A)$

The vectors representing the direction from the hip to the knee and from the knee to the ankle are:

$$\overrightarrow{HK} = (x_K - x_H, y_K - y_H, z_K - z_H) \quad (4)$$

$$\overrightarrow{KA} = (x_A - x_K, y_A - y_K, z_A - z_K) \quad (5)$$

The cosine of the knee angle θ_K is given by the dot product formula:

$$\cos(\theta) = \frac{\overrightarrow{HK} \cdot \overrightarrow{KA}}{|\overrightarrow{HK}| |\overrightarrow{KA}|} \quad (6)$$

where:

$$\overrightarrow{HK} \cdot \overrightarrow{KA} = (x_K - x_H)(x_A - x_K) + (y_K - y_H)(y_A - y_K) + (z_K - z_H)(z_A - z_K) \quad (7)$$

and

$$|\overrightarrow{HK}| = \sqrt{(x_K - x_H)^2 + (y_K - y_H)^2 + (z_K - z_H)^2} \quad (8)$$

$$|\overrightarrow{KA}| = \sqrt{(x_A - x_K)^2 + (y_A - y_K)^2 + (z_A - z_K)^2} \quad (9)$$

Thus the knee angle is obtained:

$$\theta_K = \cos^{-1} \frac{\overrightarrow{HK} \cdot \overrightarrow{KA}}{|\overrightarrow{HK}| |\overrightarrow{KA}|} \quad (10)$$

Dynamic Time Warping (DTW)

DTW is an algorithm designed to measure the similarity between two sequences that may differ in time or speed. It determines the optimal alignment between these sequences by minimizing their cumulative distance. DTW is particularly valuable in applications such as speech recognition, motion analysis, and time series comparison. For example, $S_1 = [s_1(1), s_1(2), \dots, s_1(n)]$ and $S_2 = [s_2(1), s_2(2), \dots, s_2(m)]$, where n and m represent the lengths of the discrete signals. The DTW distance is calculated using the following recursive relation:

$$DTW(i, j) = dist(S_1(i), S_2(j)) + \min \begin{cases} DTW(i-1, j) & \text{insertion} \\ DTW(i, j-1) & \text{deletion} \\ DTW(i-1, j-1) & \text{match} \end{cases} \quad (11)$$

where:

- $DTW(i, j)$ is the cumulative distance between two signals s_1 and s_2 at points i and j .
- $dist(S_1(i), S_2(j))$ is the distance between element $s_1[i]$ and $s_2[j]$ (calculated using the Euclidean distance).
- The recursive formula minimizes the sum of the current distance and the minimum distances of three possible paths: insertion, deletion, and matching.

Suppose we have two distinct signals, as shown in Figure 4, and we want to determine whether there is a difference between them using DTW. In this case, DTW will calculate the alignment between the two signals.

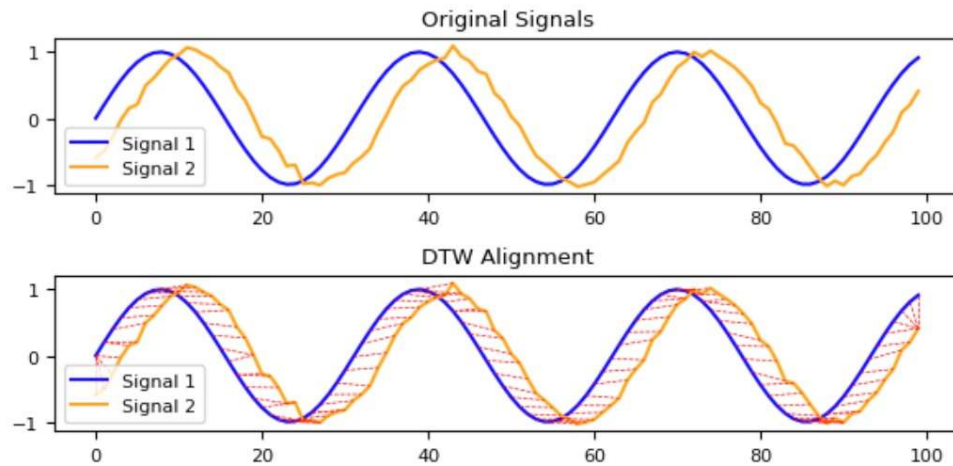


Fig. 4. Example of two signal analysed using DTW

Fatigue Detection Based on Biomechanical Signals

This research on the application of DTW for STS analysis has been explored in various studies. DTW effectively matches similar movement signals, even when there are variations in time and speed, as seen in studies using DTW to identify daily activities, such as STS (Acorn et al., 2015). In this study, DTW was used to assess the similarity of biomechanical signals in subjects before and after exercising. Generally, the assumptions made are:

- Normal Activity: Characterized by smooth and consistent changes in knee and hip flexion, with minimal lateral displacement in the X and Y coordinates of the knee and hip.
- Abnormal Activity: Abnormal movements may arise from coordination issues, muscle weakness, or other functional impairments. This can lead to unpredictable angular changes, irregular joint movement patterns, or excessive displacements that deviate from normal signals.

This study defines normal activity as the subject's STS movement before the exercise, while abnormal activity refers to the STS movement after the exercise. The classification is based on observations of changes in knee angle and DTW distance.

Results and Discussion

Knee Angle Analysis

In the STS activity experiment, the sitting position was defined as 90° and the standing position as 0° . The subject's position is shown in Figure 5. In this range, the optimal knee angle during the STS activity transitions smoothly from approximately 90° when sitting to 0° when fully standing. DTW analysis was performed using angular values for the knee angle, capturing the transition from 90° (sitting) to 0° (standing) during the STS activity. This analysis underscores the importance of evaluating the DTW range and statistical metrics to assess movement consistency, as well as to identify potential fatigue or biomechanical changes resulting from the exercise.

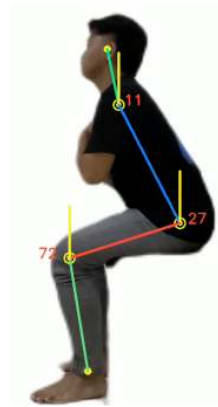


Fig. 5. Knee angle of subject 5 in STS

The standard deviation of the measurement results indicates variability in knee angle performance changes among subjects. However, this variability is manageable, suggesting a relatively consistent training effect on STS performance across participants. The knee angle measurement results can be found in Table 1.

Table 1. Knee angle before and after exercise

	before	STD	after	STD
Subject 1	40.94°	28.89°	46.37°	28.00°
Subject 2	48.53°	23.99°	45.51°	25.55°
Subject 3	51.18°	23.51°	45.77°	24.58°
Subject 4	50.81°	25.99°	51.31°	27.78°
Subject 5	48.45°	28.61°	49.72°	26.1°

The DTW distance results are as follows:

- Subject 1: 2932.78
- Subject 2: 1020.88
- Subject 3: 1489.96
- Subject 4: 2834.56
- Subject 5: 869.90

Lower DTW values suggest a more consistent movement pattern between the pre- and post-exercise STS phases. Subject 5 had the lowest DTW value, indicating more uniform movement, whereas Subject 1 had the highest DTW value, revealing a significant difference in movement between the two phases. Knee flexion signals for Subjects 1–5 are shown in Figures 6–10, highlighting a noticeable shift between the pre- and post-exercise signals.

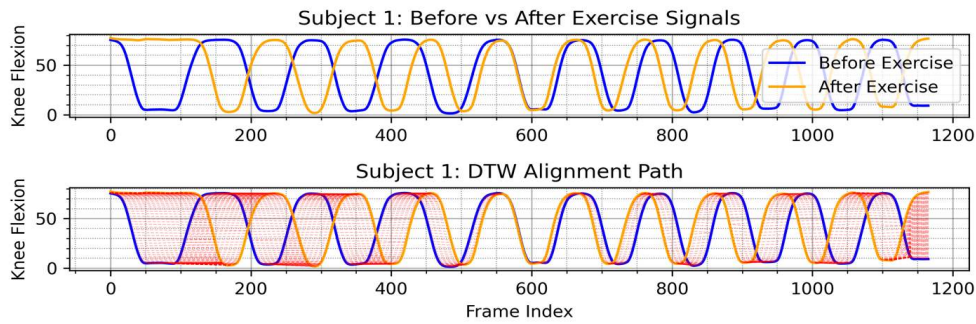


Fig. 1. Subject 1 before and after exercise signals

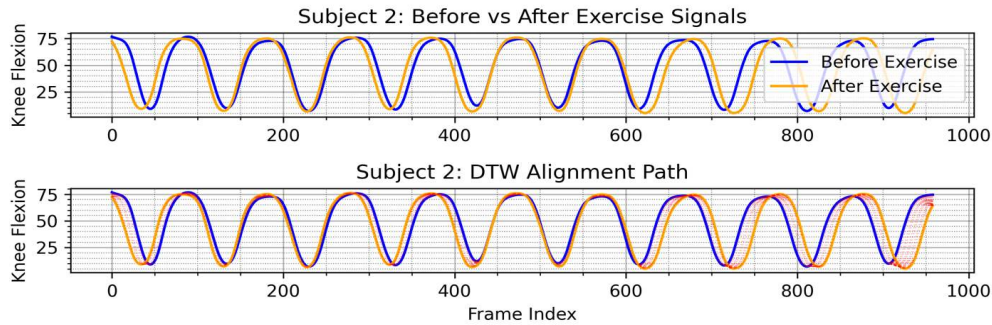


Fig. 2. Subject 2 before and after exercise signals

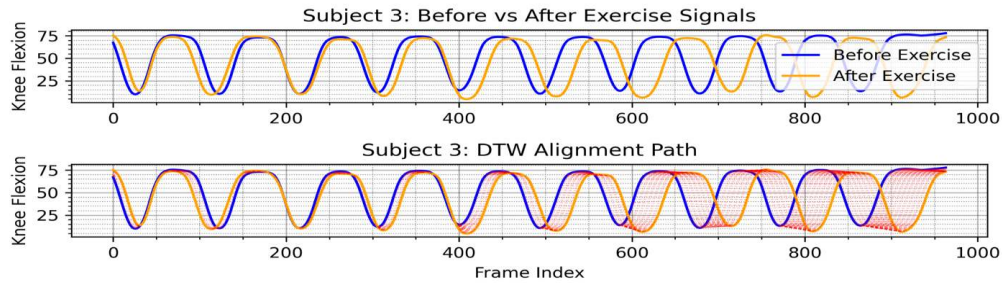


Fig. 3. Subject 3 before and after exercise signals

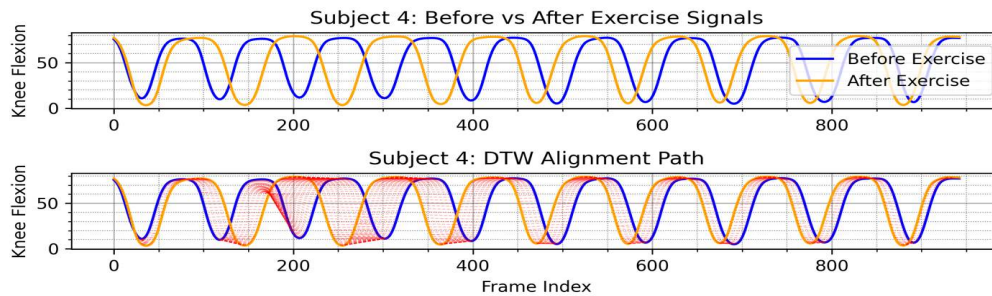


Fig. 4. Subject 4 before and after exercise signals

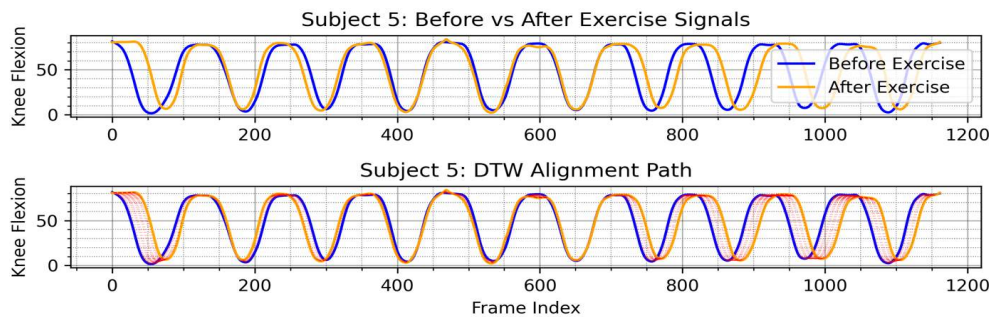


Fig. 5. Subject 5 before and after exercise signals

Knee angle interpretation:

- Subject 5 demonstrated the most consistent knee motion before and after exercise, as indicated by a lower DTW distance and relatively stable averages across the phases.
- Subject 1 demonstrated a significant difference between the "before" and "after" phases, evidenced by the highest DTW distance and a significant increase in average knee angle after exercise.
- The knee angle range should ideally transition smoothly from 90° (sitting) to 0° (standing) during the STS activity. However, deviations in the data, particularly an increase in knee angle after exercise, may suggest fatigue or changes in movement dynamics.

Smooth and consistent transitions between these angles, without excessive fluctuation, indicate effective motor control and minimal fatigue. Significant deviations from this range, particularly large differences between the pre- and post-exercise phases, may indicate muscle fatigue or reduced control over the movement. This ideal range serves as a benchmark for assessing whether the participant's movement patterns align with the expected biomechanical efficiency during the activity.

Knee Joint Trajectory Plot

The trajectory plots for the five subjects, before and after exercise, illustrate the differences in knee and hip (torso) movement patterns during the STS activity. Below is a detailed evaluation and interpretation for each subject.

Subject 1:

- Before Exercise: The knee and hip trajectories are smooth, demonstrating controlled movement from sitting to standing, with both trajectories following the expected curves.
- After Exercise: The knee trajectories appear less regular and more erratic, particularly during the stance phase. While hip trajectories exhibit some variation, they remain relatively consistent.
- Interpretation: Fatigue leads to reduced knee control, resulting in compensatory movements. In contrast, hip motion, despite being slightly affected, remains more stable.

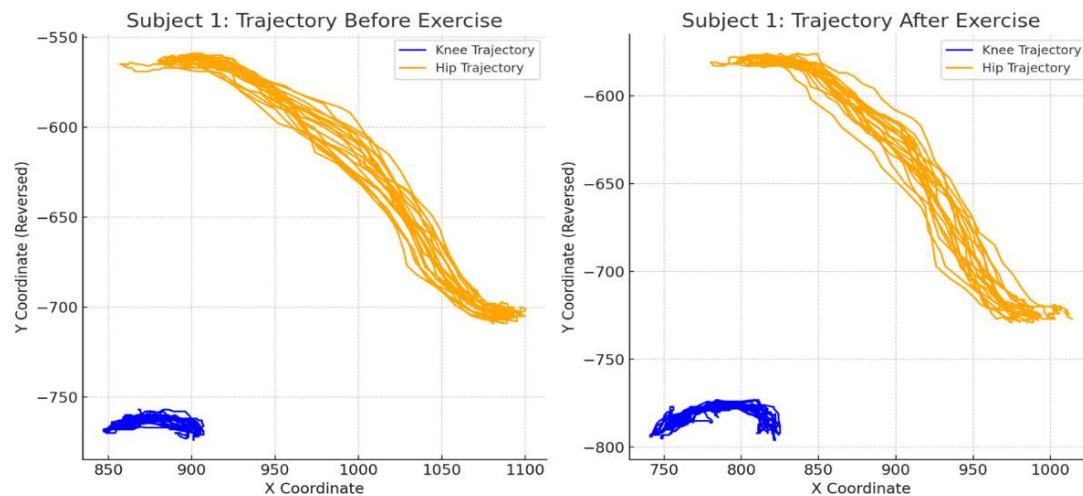


Fig. 11. Trajectory before and after training on subject 1

Subject 2:

- Before Exercise: Knee and hip trajectories show smooth, coordinated movements, reflecting effective control during the STS transition.
- After Exercise: There is a significant increase in variability in both knee and hip trajectories. The knee shows greater deviation during the upward (standing) phase, while the hip movements are less erratic in both the upward and downward phases.
- Interpretation: Post-exercise fatigue impacts knee and hip movements, resulting in greater variability and reduced coordination.

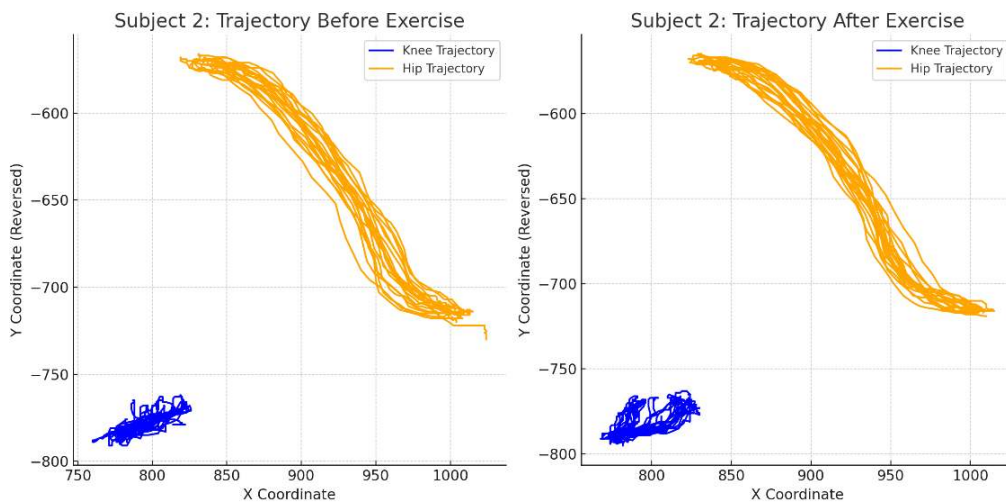


Fig. 12. Trajectory before and after training on subject 2

Subject 3:

- Before Exercise: Trajectories are smooth and predictable, indicating effective control of knee and hip movements.
- After Exercise: Knee trajectories exhibit increased variability, particularly during the transition between sitting and standing. Hip trajectories maintain relative stability but show some deviation when returning to a seated position.
- Interpretation: In summary, our study reveals that fatigue significantly impacts knee control, whereas hip trajectories remain more stable, indicating less influence on upper body movement. These important findings enhance our understanding of how exercise affects joint trajectories.

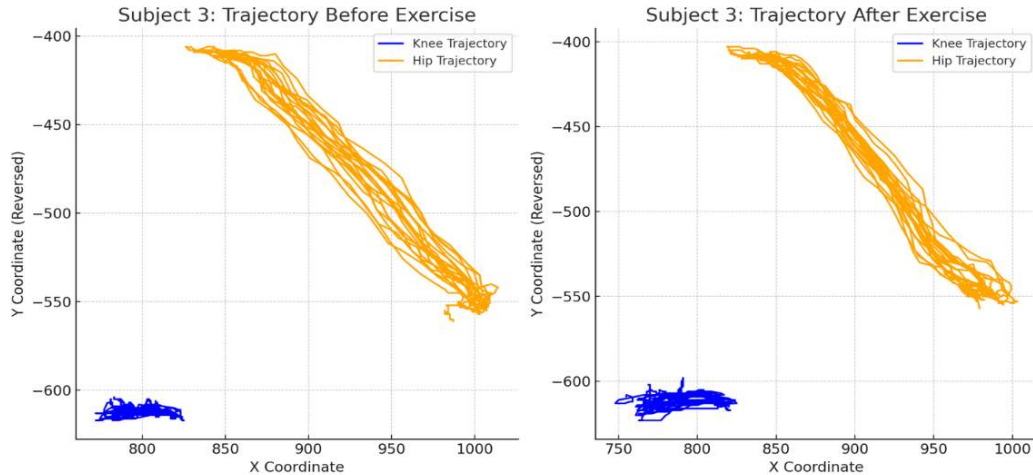


Fig. 13. Trajectory before and after training on subject 3

Subject 4:

- Before Exercise: Knee and hip movements are well-coordinated, with predictable upward and downward trajectories reflecting effective control during STS transitions.
- After Exercise: Knee trajectories show significant deviations, particularly during upward motion. Hip trajectories also become more variable, resulting in less fluid transitions between phases.
- Interpretation: Fatigue has affected knee and hip movements, leading to compensatory or erratic movements, especially in the knees, which exhibit greater deviations.

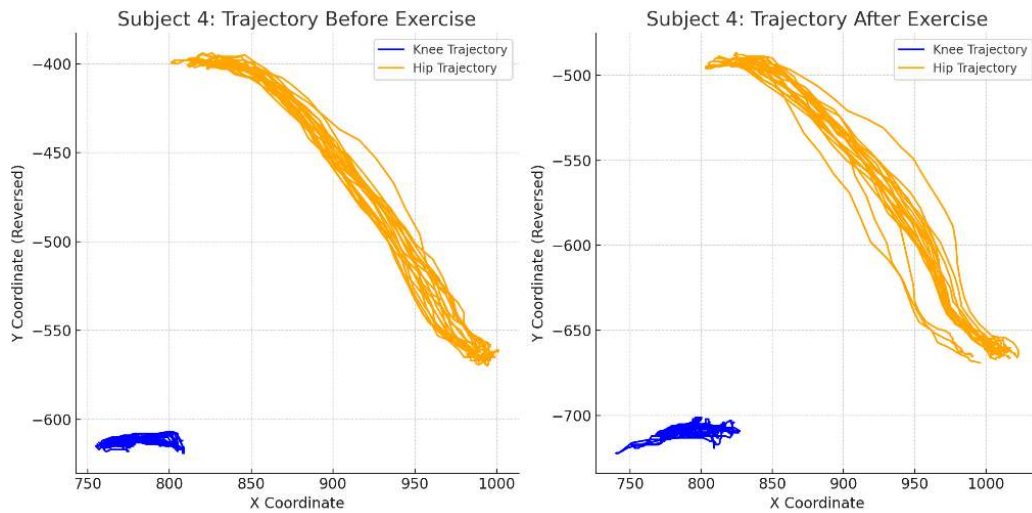


Fig.14. Trajectory before and after training on subject 4

Subject 5:

- Before Exercise: Knee and hip trajectories are smooth, and the well-coordinated movements indicate an efficient transition from sitting to standing.
- After Exercise: The knee exhibits increased variability, with greater deviations during both upward and downward phases. The hip shows some variability as well but remains more stable than the knee.
- Interpretation: The subject experienced more difficulty controlling the knee after exercise, while changes in hip movement, though less pronounced, are still observable.

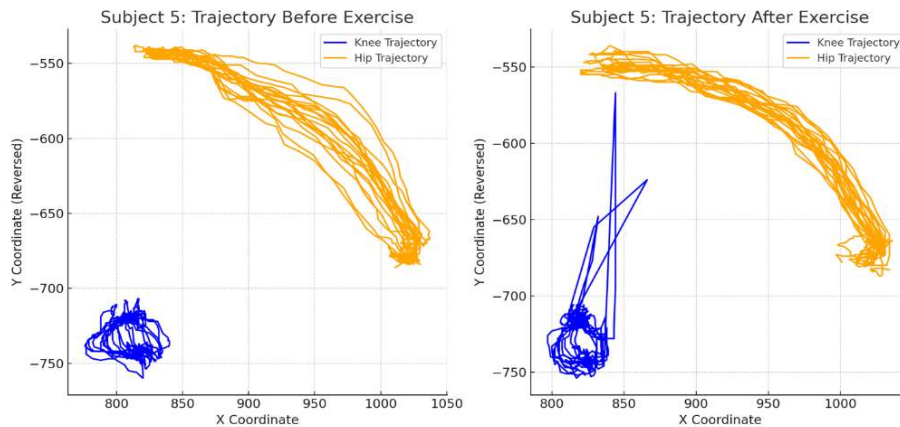


Fig. 15. Trajectory before and after training on subject 5

In the pre-exercise condition, all subjects demonstrated smooth and controlled movements during the transition from sitting to standing, reflecting strong coordination and control. In contrast, the most significant deviation occurred in the knee trajectory during the post-exercise condition, particularly in the upward (standing) phase. This indicates that fatigue has a more pronounced impact on the knee, causing compensatory or erratic movements. The hip trajectory remained generally stable, although some variability was noted owing to fatigue, particularly in Subjects 2, 4, and 5.

The proposed method uses PoseNet for key joint extraction from subject videos. Fatigue detection is achieved by analyzing the knee angle and trajectory through DTW and biomechanical analysis. The results indicate significant differences in movement consistency attributed to fatigue. This approach sets itself apart from previous studies that used IMUs or other wearable sensors (Merbah et al., 2023; Pinto-Bernal et al., 2021). In addition to IMUs, electromyogram signals have also been used for fatigue detection (Triwiyanto et al., 2017). The advantages of the proposed method include the absence of sensors attached to the subject and a relatively straightforward implementation. However, a limitation of this method is that it is specifically designed for STS movement analysis, which is used to examine certain disorders. This experiment involved a limited number of subjects, all of whom were healthy. Future research should include experiments with a larger and more diverse pool of subjects.

Conclusions

This study performed an analysis of STS activities to investigate movement patterns influenced by fatigue. Under ideal conditions, the knee angle is set at 90° while sitting and 0° when standing, with a smooth transition between these positions indicating effective motor control. DTW analysis was used to assess movement consistency before and after exercise, where lower DTW values indicate a more uniform movement pattern. The findings revealed that Subject 5 had the lowest DTW value, indicating more stable movements, whereas Subject 1 exhibited the highest value, reflecting a significant change after exercise, likely owing to fatigue. Examining knee and hip trajectories across all subjects revealed increased movement variability, particularly in the knee, after exercise, suggesting that fatigue impacts knee control more than hip control. The method used in this study involved PoseNet for key joint extraction from subject videos, providing the advantage of not requiring any attached sensors. However, this method is more tailored for STS movement analysis. While the results indicate biomechanical changes associated with fatigue, the study is constrained by a small sample size, with all participants being healthy. Therefore, additional research with a larger and more diverse participant pool is essential.

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Conflicts of interest

The authors declare no conflict of interest

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