Visual Gait Alignment for Sensorless Prostheses: Toward an Interpretable Digital Twin Framework

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Abstract

A safe and interpretable visual method for prosthetic alignment assessment is proposed, suitable for sensorless scenarios such as home rehabilitation and telemedicine. The method collects human skeletal data based on a depth camera and extracts the motion difference characteristics of the left and right legs through gait symmetry analysis. Three types of clearly structured evaluation indicators are designed, including differences in joint range of motion, differences in swing phase duration, and angular trajectory similarity, to construct an interpretable alignment scoring function. This system is designed as a front-end module of a digital twin system. The scoring results can intuitively reflect differences in wearing status, facilitating real-time evaluation and adjustment of prosthetic alignment quality. Preliminary experiments have verified the stability and practicality of this method under visual recognition conditions, laying the foundation for personalized prosthetic optimization based on digital twins.

Introduction

The accuracy of prosthesis alignment plays a decisive role in rehabilitation outcomes. Misalignment can lead to compensatory movements and increased energy expenditure, and may further result in chronic injury, gait instability, or even fall risks. In traditional rehabilitation processes, prosthesis adjustment often relies on manual assessment by experienced clinicians or prosthetists, or requires wearable sensors such as electromyography (EMG) and inertial measurement units (IMUs) for posture capture and analysis (Khamis et al. 2024). However, these approaches are costly, depending heavily on specialized personnel and equipment, and are difficult to scale in settings such as home healthcare, remote rehabilitation, or rural clinics (Malaheem, Abd Razak, and Abu Osman 2024).

Meanwhile, as artificial intelligence(AI) becomes increasingly integrated into healthcare applications, prosthetic assistance systems face new challenges—chief among them, how to ensure safety while also providing interpretable and trustworthy feedback(Le et al. 2025). In scenarios where patients must assess and adjust alignment themselves, the system's outputs not only need to be accurate, but also be understandable and usable without special training, enabling users to complete the adjustment process with clarity and confidence.

To address these challenges, a sensorless visual evaluation system for prosthesis alignment is proposed, utilizing only a standard depth camera or a lightweight digital twin system that supports real-time gait analysis and prosthesis alignment without physical contact or embedded sensors. The system employs an RGB-D camera (Kinect) to capture real-time skeletal keypoints, compares the spatiotemporal features of left and right leg motion trajectories, and detects gait asymmetry. An interpretable alignment scoring mechanism is constructed based on these differences, allowing the output to serve as either alignment adjustment guidance or remote rehabilitation assessment, even without professional supervision. At the same time, as part of the digital twin prosthesis, the system can interact with the digital twin model in real time, synchronously reproducing the patient's current gait status and prosthetic configuration in a virtual environment, supporting remote doctors or algorithm modules to perform alignment optimization and risk prediction based on simulation results, and improving the intelligence and adaptability of the system.

Compared with conventional methods, this system offers the following advantages:

- Safe and deployable: It operates without wearable or contact-based sensors, suitable for home environments;
- Interpretable evaluation: It provides direct scoring indicators and highlights specific sources of asymmetry, enhancing user understanding and trust;
- Lightweight design: The overall algorithm is simple, adaptable to edge devices or remote digital twin platforms, and supports flexible deployment.

The main contributions are summarized as follows:

- A vision-based, sensorless method for gait asymmetry evaluation using skeletal tracking is proposed;
- A multi-dimensional, interpretable metric set is designed, including differences in Range of Motion (ROM), swing duration, and trajectory similarity;
- A safe, low-cost, and visual alignment scoring system is implemented and validated in simulations, demonstrating practicality and robustness.

Related Work

The evaluation of prosthetic alignment is of great significance in the field of rehabilitation engineering, with the core goal of ensuring the stability and biomechanical rationality of the wearer's gait. Traditional methods mainly rely on professional visual observations, clinical judgement, or sensor-based detection such as electromyography (EMG)(Yadav and Veer 2023), inertial measurement units (IMU)(Samala et al. 2024), etc. Although these methods have certain guarantees in terms of accuracy, they have obvious limitations in terms of cost, ease of use, and home deployment, making it difficult to meet the needs of remote rehabilitation and home use scenarios.

In recent years, with the development of AI and computer vision technology, researchers have gradually attempted to use noncontact methods for prosthetic alignment and gait evaluation. For example, some work uses RGB or depth cameras to extract skeletal keypoints and evaluates gait stability and left-right symmetry through pose analysis(Cimorelli et al. 2024; Stenum et al. 2024). This type of method has significant advantages in terms of security and deployability and can avoid the discomfort and operational complexity brought by wearable devices. However, most existing systems still suffer from issues such as insufficient interpretability, black box scoring results, and high barriers to users' understanding, which limit their application effectiveness in actual rehabilitation processes(Lu et al. 2025).

In terms of evaluation indicator design(Olaya-Mira et al. 2025), traditional research often focuses on single angle changes or gait cycle characteristics, lacking multi-dimensional, comprehensive analysis. For example, relying solely on Range of Motion (ROM) or gait rhythm may not accurately capture the overall differences in motion patterns(Katmah et al. 2023). In addition, some methods ignore dynamic shape differences (such as trajectory morphology), making it difficult to fully reflect the impact of prosthetic wearing on natural gait(Mohammadzade et al. 2021).

In the field of explanatory modeling, a small amount of work has explored improving the interpretability of scoring results, such as using visual graphs(Aghababa and Andrysek 2024) or causal rules(Chen et al. 2022) to label types of anomalies. However, it is still relatively rare to systematically integrate multidimensional indicators into structured scoring models and provide factor-level attribution explanations. The lack of such a structured transparent scoring mechanism often weakens users' trust in system recommendations, limiting their clinical promotion and daily use.

Meanwhile, digital twin (DT) technology has attracted increasing attention in the field of rehabilitation engineering(Chen et al. 2023) due to its ability to simulate, monitor, and optimize individualized rehabilitation processes in virtual environments. Some recent studies have begun to explore the application of DTs in exoskeleton(Wang et al. 2023) or musculoskeletal analysis(Khan et al. 2023; Maksymenko et al. 2023), as well as their integration with VR and AR for rehabilitation training(Yan et al. 2022).

Although some work has introduced visual analysis and interpretable mechanisms in gait assessment, there is still a lack of systems that integrate them with digital twin prosthetic models for virtual simulation, remote feedback, and parameter optimization. To address the shortcomings of existing systems in terms of cost, interpretability, and evaluation indicators, this paper proposes a sensorless prosthetic alignment scoring system based on visual skeleton recognition. The system has three major advantages: (1) three-dimensional indicator fusion (ROM difference, swing time difference, and DTW distance); (2) structural scoring function; and (3) causal attribution graph mechanism. This provides a practical and deployable solution for prosthetic adjustment and gait assessment in home rehabilitation and remote assessment scenarios.

System Framework

This system is designed for home environments where prosthesis users require accessible alignment evaluation. As illustrated in Figure 1, the overall framework consists of three key modules:

1. Skeletal data acquisition and preprocessing: The system captures lower-limb skeletal data using a Kinect depth camera, extracting the three-dimensional coordinates of key joints(such as the hip, knee, and ankle) over time. A sliding average filter is applied to smoothen the data, resulting in a stable skeletal trajectory.
2. Asymmetry detection and feature extraction: A symmetry analysis module mirrors the right leg skeleton to align with the left leg in spatial coordinates, and calculates the offset vectors between corresponding joints. Temporal features related to gait rhythm are also extracted. Based on these, three core alignment-related features are computed to quantify individual gait asymmetry (detailed in Section 3).
3. Alignment scoring and result presentation: The extracted asymmetry metrics are normalized and combined through weighted summation to produce an overall alignment score, which reflects the deviation between the current gait and an ideal symmetrical pattern. The final output provides parameter suggestions to assist patients or clinicians with alignment adjustments (detailed in Section 4).

This system is modular, free of wearable devices, and highly interpretable, making it well-suited for remote rehabilitation, in-home assessment, or training support scenarios. Additionally, the framework is naturally compatible with digital twin platforms, enabling synchronized virtual prosthesis representations that mirror user behavior in real-time. This extension facilitates remote expert intervention, personalized optimization, and long-term rehabilitation tracking.

Importantly, rather than relying on the proprietary Kinect skeletal tracking API, our system only utilizes the depth images provided by the Kinect device. We developed a customized skeletal recognition algorithm to extract the 3D coordinates of key joints (hip, knee, ankle) directly from the raw depth frames. This design not only ensures independence from specific hardware APIs but also makes the framework adaptable to other RGB-D cameras, further strengthening its portability and long-term applicability.

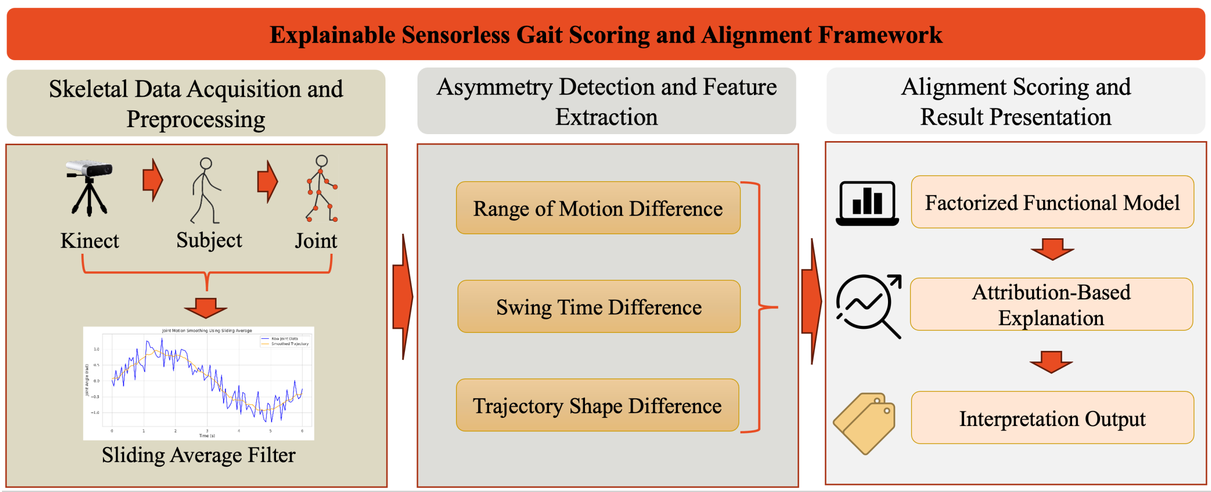

Figure 1: System framework for sensorless gait alignment scoring and interpretation.

Alignment Evaluation Metrics

To enable quantitative analysis of gait conditions in prosthesis users, this system defines three simple, intuitive, and interpretable alignment metrics based on visual skeletal data, focusing on dynamic differences between the left and right legs. These three metrics were selected because they capture complementary aspects of gait: Range of Motion Difference represents spatial amplitude deviation, Swing Time Difference captures temporal rhythm, and Trajectory Shape Difference quantifies spatiotemporal trajectory similarity. Together, they cover the major biomechanical factors of gait asymmetry identified in clinical literature.

Range of Motion(ROM) Difference

Range of Motion (ROM) refers to the angular difference between the maximum and minimum joint positions within a gait cycle. The system calculates the ROM of the knee joint for both legs and uses their difference as a measure of asymmetry. This metric helps identify whether the prosthetic side exhibits limited mobility or reduced motion amplitude. The ROM is computed as:

$$\mathrm{ROM}_j = \max_t \theta_j(t) - \min_t \theta_j(t)$$

where $\theta_j(t)$ denotes the knee joint angle of leg $j \in \{\text{left}, \text{right}\}$ at time t. The absolute difference between the ROM values of both legs is then calculated as:

$$\Delta\mathrm{ROM} = |\mathrm{ROM}_{\text{left}} - \mathrm{ROM}_{\text{right}}|$$

This metric reflects the amplitude of joint motion. A reduced ROM on the prosthetic side may indicate limited flexibility, insufficient activation, or misalignment of the prosthesis.

Swing Time Difference

By tracking the vertical (Z-axis) displacement of the ankle joint, the system identifies the start and end points of each leg's swing phase and calculates the duration difference between them. This metric reflects the rhythmic consistency of bilateral gait, which may be disrupted during early prosthesis use or under fatigue.

Let $T_{\text{swing},j}$ represent the swing duration of leg j. The swing time difference is given by:

$$\Delta T_{\text{swing}} = |T_{\text{swing,left}} - T_{\text{swing,right}}|$$

This temporal metric captures rhythm asymmetry between the legs. Significant deviations may arise during early prosthesis adaptation, neuromuscular imbalance, or fatigue.

Trajectory Shape Difference

To compare the temporal patterns of joint motion, the system applies Dynamic Time Warping (DTW) to the joint angle sequences of the two legs. DTW tolerates variations in speed and provides a distance measure of sequence similarity, making it suitable for assessing synchronization of joint movement patterns.

Let $\theta_{\text{left}}(t)$ and $\theta_{\text{right}}(t)$ be the sequences of joint angles for the left and right knees, respectively. The DTW distance is computed as:

$$\mathrm{DTW}(\theta_{\text{left}}, \theta_{\text{right}}) = \min_W \sum_{(i,j)\in W} \|\theta_{\text{left}}(i) - \theta_{\text{right}}(j)\|$$

where W is a warping path that aligns the two sequences in a non-linear time domain. The DTW distance captures overall shape similarity, while being tolerant to local speed differences.

Together, these three metrics capture gait asymmetry from the perspectives of amplitude(ΔROM), rhythm(ΔT_{swing}), and shape(DTW distance). They serve as the main components of the alignment scoring function. In subsequent modules, the metrics are normalized and integrated into an overall score that provides an interpretable representation of the current alignment state.

Structurally Interpretable Alignment Scoring Model

To enhance the system's transparency, explainability, clinical usability, and real-time feedback capabilities, we propose a structurally interpretable alignment scoring model. Unlike the traditional approach of treating alignment scores as black-box scalars, we decompose them into three functional dimensions: spatial, temporal, and spatial-temporal. Each dimension corresponds to a specific type of biomechanical deviation. This causal structure not only provides quantitative assessment results but also provides interpretable support for diagnostic analysis. This significantly enhances users' understanding of the prosthesis and facilitates its adjustment.

Factorized Functional Model Let the final alignment score be denoted as $S \in [0, 1]$, with higher values corresponding to better gait alignment and lower asymmetry across spatial, temporal, and spatiotemporal dimensions. To compute this score, we rely on three core normalized asymmetry metrics that capture distinct aspects of gait deviation:

$$x_1 := \Delta\text{ROM}, \quad x_2 := \Delta T_{\text{swing}}, \quad x_3 := D_{\text{DTW}}$$

These metrics respectively correspond to the following structural deviation types:

- x_1: **Joint Deviation** — Reflects reduced range of motion or joint constraint.
- x_2: **Temporal Imbalance** — Captures asymmetry in rhythmic timing between limbs.
- x_3: **Pattern Drift** — Measures sequence-level dissimilarity in joint trajectories.

We model the score as a structured aggregation function:

$$S = \mathcal{F}(x_1, x_2, x_3)$$

A simple yet interpretable instantiation of $\mathcal{F}$ is a weighted additive form:

$$S = \frac{1}{1 + w_1 x_1 + w_2 x_2 + w_3 x_3}$$

$$\text{subject to} \quad w_i \geq 0, \quad \sum_{i=1}^{3} w_i = 1$$

where w_i denotes the importance weight for each structural factor. In the current implementation, we adopt uniform weights ($w_1 = w_2 = w_3 = \frac{1}{3}$) as a simple and interpretable baseline. This choice ensures fairness across factors without requiring additional assumptions. In future work, we plan to explore expert-informed strategies and convex optimization methods to learn adaptive weights from multi-subject data, making the framework more clinically relevant and personalized.

Attribution-Based Explanation To enable interpretability, we decompose the alignment score into per-factor contributions:

$$C_i = w_i x_i$$

Each $C_i = w_i x_i$ serves as a localized attribution term, quantifying how much the corresponding asymmetry metric contributes to the overall alignment error. The total error is defined as:

$$E = \sum_{i=1}^{3} C_i = w_1 x_1 + w_2 x_2 + w_3 x_3$$

and the alignment score is computed as:

$$S = \frac{1}{1 + E}$$

Thus, a higher C_i indicates that the corresponding structural deviation (e.g., range of motion difference, swing time difference, or trajectory mismatch) plays a larger role in reducing the alignment score. The attribution vector $\mathbf{C} = (C_1, C_2, C_3)$ reflects the composition of the total error and can be visualized using radar plots or bar charts to support intuitive interpretation and assist clinical diagnosis.

Interpretation Output We further categorize alignment errors into semantic tags:

$$\text{Cause}(S) = \begin{cases} \text{Joint limitation}, & C_1 > \max(C_2, C_3) \\ \text{Rhythm inconsistency}, & C_2 > \max(C_1, C_3) \\ \text{Trajectory deviation}, & C_3 > \max(C_1, C_2) \end{cases}$$

This logical rule-based interpretation enables the system to output diagnostic explanations such as: *"The primary source of misalignment is temporal imbalance, likely due to inconsistent swing timing between the legs."*

At the same time, we are actively exploring additional semantic categories and feedback mechanisms, so that the system can provide richer guidance and more clinically meaningful suggestions in future iterations.

Experiments and Preliminary Results

To evaluate the effectiveness of the proposed system, we constructed a pilot experimental setup using an Azure Kinect camera to capture lower-limb motion data. The three alignment evaluation metrics introduced above were analyzed both visually and quantitatively. This study involved one subject as a preliminary pilot evaluation. The goal is to demonstrate feasibility rather than clinical validation.

Experimental Setup

The subject, wearing a prosthetic limb, walked back and forth on a smart treadmill. The Kinect device was positioned approximately 1 meter in front of the subject and captured skeletal data at 30 frames per second. Importantly, we did not rely on the proprietary Kinect skeletal tracking API. Instead, we developed a self-designed pose estimation algorithm to extract the 3D coordinates of key joints (hip, knee, and ankle) directly from raw depth images, as illustrated in Figure 2. Multiple consecutive gait cycles were collected to ensure the representativeness of the evaluation.

Visualization and Metric Analysis

Figure 3 shows the angular variation of the left and right knee joints over multiple gait cycles. The prosthetic knee

Figure 2: Joint detection result using the proposed non-contact vision-based method. The hip, knee, and ankle joints are accurately located and visualized.

exhibits a greater range of motion during some cycles, even exceeding that of the unaffected knee. This suggests over-compensation or unstable control of joint motion after wearing the prosthesis, further confirming the necessity of gait alignment.

The prosthetic side (left leg) exhibits a greater range of motion than the unaffected side over multiple cycles, with multiple local peaks, reflecting abnormal amplitude fluctuations during gait control.

Figure 4 shows a cycle-by-cycle comparison of the left and right knee range of motion (ROM) over multiple gait cycles. The green curve represents the prosthetic side, the orange curve represents the unaffected side, and the blue curve represents the difference ΔROM , between the two. Overall, the ROM of the prosthetic side is higher than that of the unaffected side in most cycles, suggesting a greater oscillation amplitude to compensate for gait instability or insufficient actuation.

Of particular note is the sharp increase in ΔROM values during cycles 2 and 9, reflecting a significant increase in the inconsistency between the prosthetic and unaffected leg range of motion. This may be due to factors such as wearing error, discomfort, subject fatigue, or postural changes. This metric is highly sensitive in revealing dynamic gait symmetry.

In Figure 5, we conducted statistical analysis on the range of motion (ROM) of the knee joint on the prosthetic side, healthy side, and between the two, and presented it in the form of mean ± standard deviation. The results showed that the average ROM on the prosthetic side (31.1 °) was slightly higher than that on the healthy side (25.0 °), indicating that prosthetic users may compensate for the effects of unstable posture or insufficient drive by using larger knee joint swings during movement. Meanwhile, the average value of ΔROM(the difference between the two side ROMs) is 9.2 °, which reflects the overall level of gait asymmetry. It is worth noting that the standard deviations of all indicators are relatively large, indicating significant differences between subjects in different gait cycles. Analyzing these differences is the foundation for subsequent prosthetic alignment optimization, clinical decision-making assistance, or personalized rehabilitation recommendations generation.

Figure 6 shows the swing time trends for the prosthetic and unaffected knee joints during each gait cycle. The green line represents the time difference ($\Delta\mathrm{Swing}$) between the two, which can be used to measure gait asymmetry in rhythm. Overall, the unaffected side is slightly longer than the prosthetic side in most cycles, with the difference ranging from 0 to 10 frames, indicating a certain degree of gait rhythm difference.

Figure 7 shows the shape similarity of the left and right knee joint motion trajectories, measured using the DTW distance. The results show significant differences in the shape of the gait trajectories between the two sides, indicating that, in addition to rhythm, the movement pattern on the prosthetic side also exhibits different gait structural characteristics.

Alignment Score and Interpretability Visualization

Based on metrics such as ΔROM, ΔT_{swing} and D_{DTW}, the gait performance of prosthetic users can be evaluated across spatial, temporal, and spatiotemporal dimensions, enabling the generation of a prosthesis alignment score.

Figure 8 shows the alignment scores calculated by the system over multiple gait cycles. It can be seen that most of the cycle scores are at a high level (> 0.8), but there are still a few cycles (such as the 2nd, 9th and 13th cycles) where the scores significantly decrease, indicating that there are significant differences in the movement amplitude, rhythm, or trajectory shape of the legs at this time, which may be related to factors such as changes in the wearer's posture, delayed prosthetic response, or soft tissue oscillation.

To enhance the interpretability of the alignment scoring model, this paper further conducted attribution visualization analysis on the scoring components of each gait cycle, as shown in Figure 9. Each bar chart in the figure corresponds to a gait cycle, which is internally decomposed by color into the attribution contributions of three structural deviation indicators: joint range of motion difference (ROM), swing time difference (Swing), and trajectory deviation (DTW). The height of each section represents the degree of influence of the corresponding indicator on the total error ($C_i = w_i x_i$), which can intuitively reveal the dominant sources of anomalies in different periods.

Safety and Interpretability

Compared to traditional methods that rely on wearable devices such as manual evaluation, electromyography (EMG), or inertial measurement units (IMU), the system proposed in this paper can provide prosthetic alignment feedback under completely contactless conditions, significantly improving user comfort and eliminating the tedious process of sensor wearing and calibration. Especially for users of prosthetics in remote healthcare, the self debugging process is a great advancement.

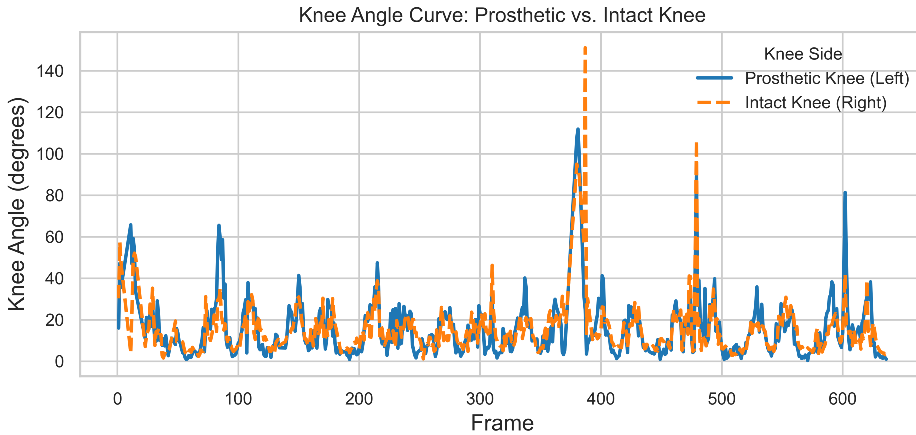

Figure 3: A graph showing the change in left and right knee joint angles over time (frame number).

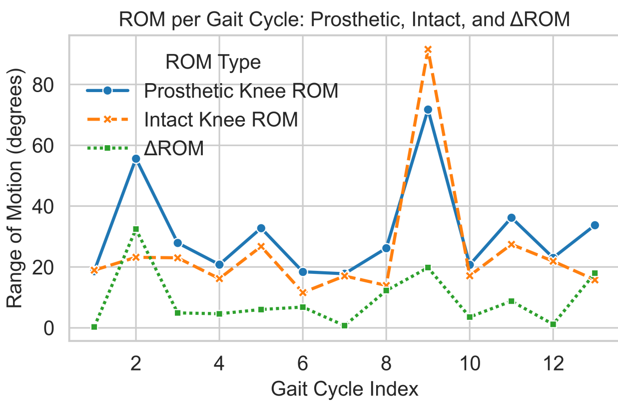

Figure 4: Per-Gait-Cycle Analysis of Prosthetic and Intact Knee ROM

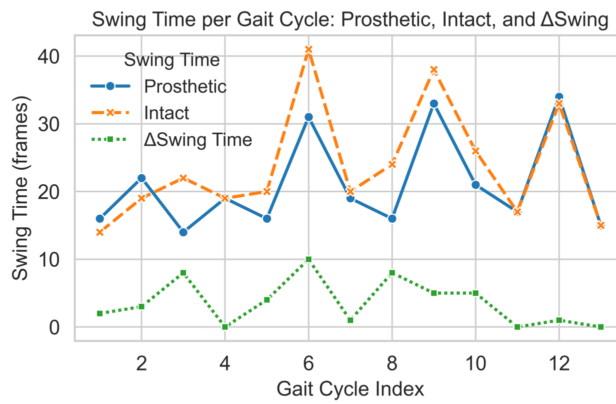

Figure 6: Swing time comparison between the prosthetic and intact limbs across gait cycles. $\Delta\mathrm{Swing}$ denotes the absolute difference in swing duration between the two sides, reflecting rhythm asymmetry.

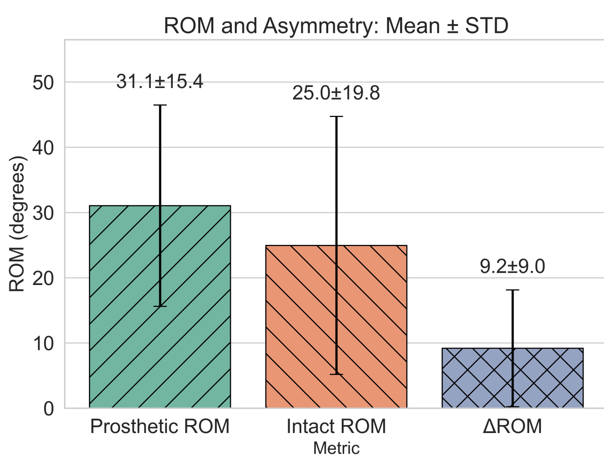

Figure 5: Per-Mean and Standard Deviation of Knee ROM Metrics Across Gait Cycles

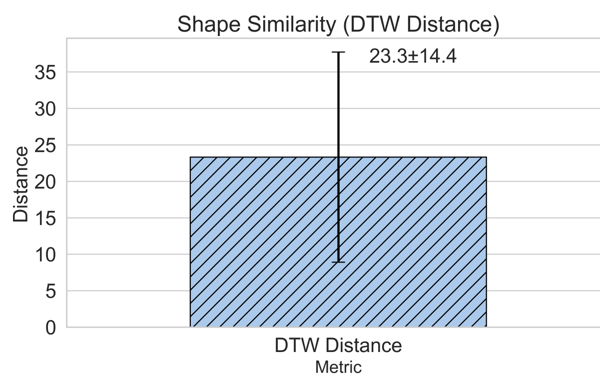

Figure 7: Shape similarity between prosthetic and intact knee joint trajectories measured by DTW distance. A higher DTW value indicates greater divergence in motion shape between the two sides.

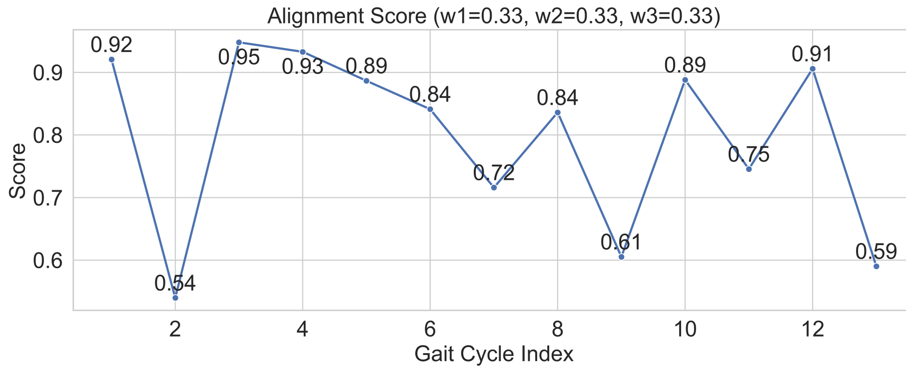

Figure 8: Alignment score over gait cycles. Higher values indicate better gait symmetry.

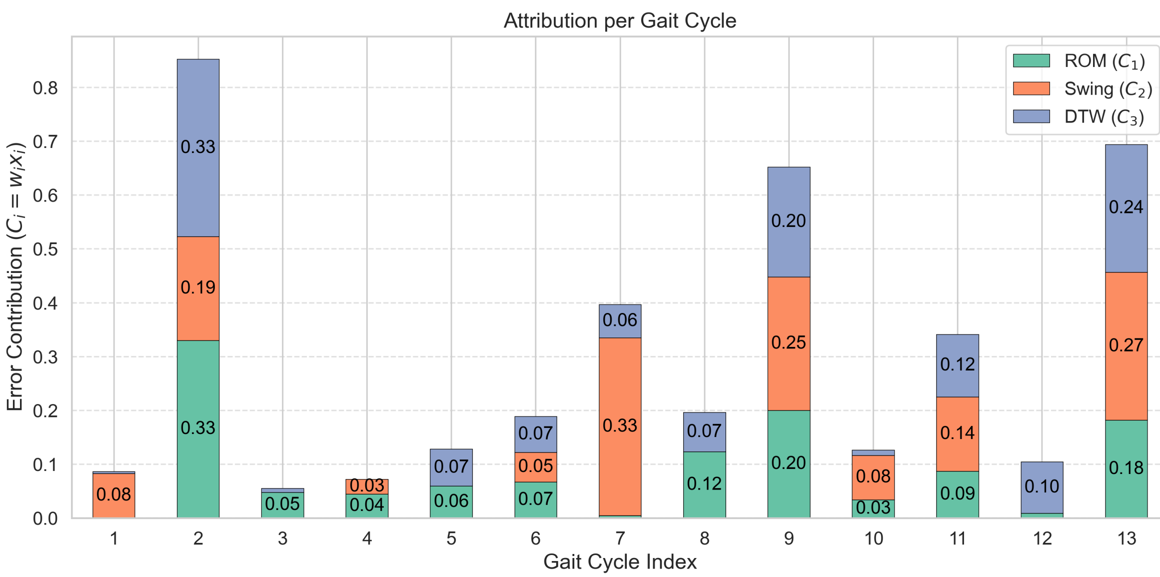

Figure 9: Visualization of Alignment Score Attribution for Each Gait Cycle. The bar chart represents the contribution values of three types of structural errors, ROM ($C1$), Swing ($C2$), and DTW ($C3$), in three color segments. The numerical annotations show the specific impact size of each indicator.

The three evaluation indicators proposed in the system, Range of Motion, Swing Time, and Trajectory Similarity, are presented in visual form to facilitate users and clinical doctors to understand the basis for system scores. This good interpretability not only enhances users' trust in system recommendations, but also helps them form a visual understanding of their own prosthetic usage status, thereby achieving spontaneous adjustment and intervention. The semantic tags (e.g., joint limitation, rhythm inconsistency) are currently derived from biomechanical reasoning, and future validation with clinical experts will be conducted to ensure medical reliability.

In addition, the intermediate process parameters output by the system have clear physical meanings and can be naturally embedded into the prosthetic digital twin framework as observation states to participate in virtual simulation, model optimization, and personalized adjustment. This fusion provides a foundation for building intelligent digital twin prostheses with adaptive capabilities, further promoting the continuous evolution of prosthetic alignment evaluation and remote rehabilitation support.

Conclusion and Future Work

A sensorless alignment evaluation system for prosthesis users was presented in this work. Based on Kinect visual input, the system identifies key skeletal points throughout the body, but especially in the lower limbs and calculates an alignment score using three interpretable metrics: range of motion (ROM), swing time, and trajectory similarity. The overall framework is simple, cost-effective, and offers good safety and interpretability, making it suitable for home rehabilitation and remote support scenarios.

Preliminary experiments show that the system effectively captures asymmetry changes during prosthesis use. The alignment scores are stable and informative. Compared with traditional methods, the proposed approach demonstrates advantages in user experience, ease of deployment, and real-time feedback.

Future work will focus on the following directions:

- Incorporating data from more subjects to evaluate robustness across user groups and prosthesis types;
- Porting the system to mobile or tablet platforms to enable portable rehabilitation support;
- Integrate the system with the prosthetic digital twin framework to achieve personalized model updates, simulation based alignment diagnosis, and long-term rehabilitation tracking;

Looking ahead, we plan to expand the scale of evaluation to a larger group of prosthesis users with diverse demographics and prosthetic types, in collaboration with clinicians, to establish robustness and generalizability.

Ethical Statement

All participants involved in this study provided written informed consent prior to data collection. The experiment was conducted in accordance with institutional ethical guidelines. No invasive procedures were involved. The study only utilized external video recordings captured via a depth camera, and no physical contact or intervention was applied to the participants. The experimental protocol posed no risk to the health or safety of the subjects.

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