Gait Deviation Index for Assessing Kinematic Adaptations to Speed Variations in Human Walking

Dumitru I. Caruntu(✉) and Alfirio Trejo

University of Texas Rio Grande Valley, Edinburg, TX 78539, USA
dumitru.caruntu@utrgv.edu

Abstract. This work investigates tibiofemoral joint kinematic deviations across two walking conditions, Normal, and Fast, using the Gait Deviation Index (GDI). The primary objective was to assess the sensitivity of the GDI to variations in speed with a focus on intra-subject comparisons. Motion capture data from one healthy adult was recorded using a Vicon system and analyzed using a Joint Coordinate System (JCS) framework. Gait cycles for both conditions were segmented based on heel strike events and time-normalized to enable consistent comparison. The knee flexion angle for each cycle was computed. Singular Value Decomposition (SVD) was applied exclusively to control data from the normal condition to extract dominant mode shapes. Gait Deviation Index scores were then computed for each stride during the Fast walking condition relative to the Normal walking. The resulting average GDI score for the fast condition was approximately 88.89, which falls close to one standard deviation of the reference value of 100. This suggests that although the amplitude of joint angles differed, the underlying movement patterns remained largely consistent across conditions. These findings highlight the GDI score as a sensitive and interpretable method for detecting kinematic inconsistency induced by walking speed.

Keywords: Tibiofemoral flexion-extension · Fast versus Normal walking · Rehabilitation

1 Introduction

Human gait is a highly coordinated, three-dimensional motor task that reflects the complex interplay of the musculoskeletal and nervous systems. Subtle deviations in joint kinematics can signal compensatory strategies, biomechanical inefficiencies, or underlying pathology. Quantifying these deviations in a way that is both sensitive and interpretable remains a critical challenge in biomechanics. Among the tools developed to address this, the Gait Deviation Index (GDI) has emerged as a widely accepted metric to summarize overall gait quality using a reduced set of orthogonal gait patterns derived from high-dimensional joint kinematic data [1].

The GDI is typically computed through dimensionality reduction techniques such as Singular Value Decomposition (SVD) or Principal Component Analysis (PCA). These

N. Herisanu and V. Marinca (Eds.): AVMS 2025, SPPHY 345, pp. 171–180, 2025.
https://doi.org/10.1007/978-3-032-10786-2_16

techniques allow for the decomposition of gait waveforms into a series of ranked orthogonal modes that capture dominant patterns of variability [2]. In the original formulation by Schwartz et al. [1], the GDI was based on projecting an individual's gait data onto a normative basis constructed from healthy control strides, and deviations were quantified in terms of Euclidean distance from the mean control representation.

Recent advances have highlighted the potential of customizing the SVD basis to specific populations, improving sensitivity to deviations within targeted cohorts [3]. Building on this framework, the present study investigates how walking speed influence tibiofemoral joint kinematics in healthy individuals. Rather than applying SVD to the combined dataset, the SVD basis was computed exclusively from the Normal walking condition, enabling the assessment of the alignment relative to a subject's own typical gait or to a matched control group.

This paper reports a comprehensive analysis of gait deviation across two conditions, namely Fast walking and Normal walking, for a single subject, offering individual-level insights and implications. Mode shapes from the SVD decomposition are presented to provide a deeper understanding of how deviations manifest relative to dominant gait patterns. Ultimately, this work aims to advance the application of mode-based gait analysis for early detection of deviations, subject-specific gait monitoring, and future integration into clinical decision-making frameworks.

2 Methodology

2.1 Experimental Setup

Motion data were collected using a Vicon optical motion capture system (Vicon Motion Systems Ltd., Oxford, UK) operating at a sampling rate of 100 Hz. The system was calibrated prior to each session to ensure sub-millimeter accuracy in marker tracking. Reflective markers were placed on key anatomical landmarks including the greater trochanter, medial and lateral femoral epicondyles, medial and lateral malleoli, and the tibial tuberosity, supplemented by rigid clusters mounted on the mid-thigh and mid-shank. All trials were performed over a flat, unobstructed walkway under laboratory conditions. The subject walked without shoes. Subjects self-selected their speed based on prompts given to them before the exercise to capture natural walking patterns. The prompts were:

- Normal: "Walk as you would normally."
- Fast: "Walk as if you were late to an important meeting."

2.2 Data Processing

Marker trajectories were processed using Vicon Nexus software and exported into MATLAB (The MathWorks, Inc., Natick, MA, USA) for further analysis. Raw marker data were filtered using a fourth-order low-pass Butterworth filter, with optimal cutoff frequencies selected via residual analysis. Knee joint angles were computed following a Joint Coordinate System (JCS) framework based on the definitions of Grood and Suntay [4] and Caruntu and Hefzy [5]. The clinical angles were calculated using the modified flexion angle formula from Dabirrahmani et al. [6]. Gait cycles were segmented from heel strike to heel strike, normalized to 1001 data points representing every 0.1% from the 0–100% of the gait cycle, and organized into matrices where each column represented a full stride.

2.3 Singular Value Decomposition (SVD)

To characterize the primary patterns of knee joint kinematics during normal gait, Singular Value Decomposition (SVD) was applied to the control dataset. This decomposition facilitates the identification of dominant modes of variation within the gait cycles, enabling a compact representation of the data.

Given a data matrix $X \in \mathbb{R}^{nxp}$, where each column represents a time-normalized gait cycle comprising n time points and p strides, the SVD is defined as:

$$X = U \Sigma V^T \tag{1}$$

where:

- $U \in \mathbb{R}^{nxn}$ is an orthogonal matrix whose columns are the left singular vectors, representing the temporal patterns (mode shapes) of the data.
- $\Sigma \in \mathbb{R}^{nxp}$ is a diagonal matrix containing the singular values σ_i, which quantify the contribution of each corresponding mode to the overall variance in the data.
- $\mathrm{V} \in \mathbb{R}^{pxp}$ is an orthogonal matrix whose columns are the right singular vectors, representing the projection of each stride onto the mode shapes.

The singular values σ_i were squared to obtain the variance explained by each mode:

$$Variance_i = \sigma_i^2 \tag{2}$$

The cumulative variance accounted for (VAF) by the first m modes was then calculated as:

$$VAF(m) = \frac{\sum_{i=1}^{m} \sigma_i^2}{\sum_{i=1}^{p} \sigma_i^2} \tag{3}$$

To determine the optimal number of modes m_{optim} required to capture at least 99% of the total variance, the smallest m satisfying $VAF(m) \geq 0.99$ was identified. The corresponding truncated matrices $U \in \mathbb{R}^{nxm_{optim}}$, $\Sigma \in \mathbb{R}^{m_{optim}xm_{optim}}$,

$\mathrm{V} \in \mathbb{R}^{pxm_{optim}}$ were then extracted to form the reduced-order model:

$$X_{m_{optim}} = U_{m_{optim}} \Sigma_{m_{optim}} V_{m_{optim}}^T \tag{4}$$

This reduced representation preserves the most significant features of the control gait data, facilitating subsequent analyses such as the computation of GDI.

2.4 Gait Deviation Index Calculation

To quantify deviations from the normal gait pattern, the Gait Deviation Index (GDI) was computed following the methodology described by Schwartz and Rozumalski [1].

First, the control and experimental gait strides were projected onto the orthonormal basis U derived from the Singular Value Decomposition (SVD) of the control data. This projection yielded feature coefficient matrices $C_{control}$ and $C_{condition}$, defined as:

$$C_{control} = X_{control}^{T} U \tag{5}$$

$$C_{condition} = X_{condition}^{T} U \tag{6}$$

where $X_{control}^{T}$ and $X_{condition}^{T}$ represent the time-normalized knee flexion angle matrices for the control and experimental strides, respectively, and each column of U corresponds to a mode shape. In this study, the control condition is the Normal walking speed, and the experimental condition is the Fast walking speed.

Next, the mean feature vector of the control group, $C_{controlmean}$, was computed by taking the mean of $C_{control}$ across all control strides:

$$C_{controlmean} = mean(C_{control}) \tag{7}$$

The Euclidean distance between each experimental stride's feature vector and the mean control feature vector was then calculated to assess how far each experimental stride deviated from the control gait pattern:

$$d_{condition} = C_{condition} - C_{controlmean} \tag{8}$$

Similarly, the Euclidean distance was computed for each control stride relative to the control mean:

$$d_{control} = C_{control} - C_{controlmean} \tag{9}$$

These distances were then transformed by taking the natural logarithm to stabilize variance and improve normality:

$$GDI_{conditionraw} = \ln(d_{condition}),\ GDI_{controlraw} = \ln(d_{control}) \tag{10}$$

The mean and standard deviation of the log-transformed control distances were calculated:

$$\mu_{controlraw} = mean(GDI_{controlraw}) \tag{11}$$

$$\sigma_{controlraw} = std(GDI_{controlraw}) \tag{12}$$

Using these values, z-scores for each experimental stride were computed:

$$z_{GDI} = \frac{GDI_{conditionraw} - \mu_{controlraw}}{\sigma_{controlraw}} \tag{13}$$

Finally, the GDI for each experimental stride was calculated by rescaling the z-scores according to the original GDI framework:

$$GDI = 100 - 10(z_{GDI}) \quad (14)$$

In this formulation, a GDI of 100 corresponds to a gait pattern identical to the control mean. Each 10-point decrease in GDI corresponds to one standard deviation of deviation from the control gait pattern. Strides with GDI scores below 90 are typically considered to show clinically meaningful deviations from normal gait.

3 Results

3.1 Flexion-Extension Patterns Across Strides

The tibiofemoral flexion angle was evaluated across all recorded strides to characterize baseline motion patterns and identify deviations introduced by increased walking speed. Figure 1 shows the knee flexion angle plotted as a function of gait cycle percentage for both control (Normal walking) and experimental (Fast walking) conditions. Strides from the control condition, shown in blue, demonstrated a highly consistent progression through the gait cycle, with typical features including initial tibiofemoral flexion angle following heel strike, gradual extension during mid-stance, and a pronounced peak flexion during swing phase near 70% of the gait cycle.

In contrast, strides from the Fast walking condition, shown in orange, exhibited consistent patterns across strides but with systematic differences in flexion angle magnitudes compared to control strides. Specifically, these strides displayed higher flexion angles immediately following heel strike, indicating an increased degree of shock absorption at initial contact. The transition into terminal swing occurred earlier in the gait cycle, resulting in a leftward shift in the timing of peak flexion. Additionally, flexion angles at both the beginning (heel strike) and the end (pre-swing) of the gait cycle were elevated relative to control, while the flexion values during the foot-flat phase (approximately 10–40% gait cycle) indicate the shortening of that phase. These results suggest that increased walking speed introduced shifts in the timing of flexion peaks in the entire gait while preserving the general signature of the knee flexion angle trajectory.

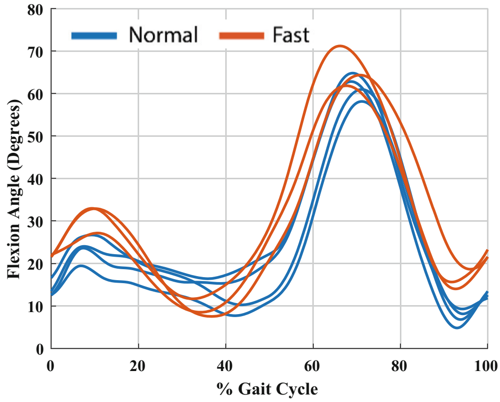

Fig. 1. Tibiofemoral flexion angles across the gait cycle for Normal and Fast speed strides. Experimental strides display higher initial flexion following heel strike, earlier transitions into terminal swing, and elevated flexion values at both initial contact and pre-swing phases. The foot-flat region experienced a shortening of that phase.

3.2 Dominant Modes of Variation in Control Data

Singular Value Decomposition (SVD) was applied to the control (Normal walking) flexion angle data to identify the dominant modes of variation during the gait cycle. Figure 2 illustrates the first few mode shapes, each scaled by their corresponding singular values to reflect their relative contribution to the total variance.

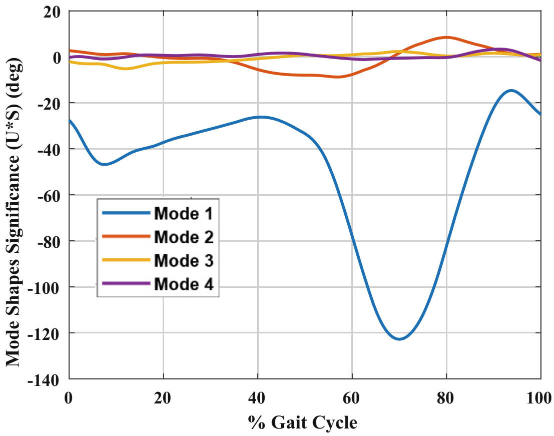

Fig. 2. Dominant flexion-extension mode shapes extracted from control strides via Singular Value Decomposition (SVD). Each mode shape is scaled by its singular value, illustrating its relative contribution to the overall variance in normal gait patterns.

The first mode accounted for most of the variance and captured the primary flexion angle behavior of the knee, including the flexion following heel strike, the subsequent extension phase during mid-stance, and the peak flexion during swing. This mode represented the global structure of knee motion and dominated the control gait pattern. The second mode captured finer adjustments, including subtle shifts in the timing and amplitude of peak flexion during swing phase. The third and subsequent modes reflected smaller, localized deviations, such as variations in the rate of flexion increase during swing or minor adjustments during early stance.

The cumulative variance accounted for (VAF) analysis indicated that only the first mode was necessary to explain over 99% of the total variance in the control strides.

3.3 Gait Deviation Index Scores

GDI was computed for each stride to quantify deviations from the normal walking pattern based on the reduced-order control model. Figure 3 displays the GDI scores grouped by walking condition. Control strides exhibited high GDI values, with scores ranging from 91.6 to 113.6 and a mean GDI of 100 ± 10. This range indicates minimal deviations from the control feature space, consistent with typical variability in normal gait.

In contrast, experimental strides collected during fast walking showed systematically lower GDI scores, ranging from 86.02 to 92.5, with a mean GDI of 88.9 ± 3.1.

Several experimental strides fell below the commonly accepted clinical threshold of 90, suggesting the presence of substantial deviations from normal flexion-extension patterns. These lower scores reflect both phase shifts and structural shape changes induced by the faster walking speed, consistent with observations of earlier terminal swing and increased flexion amplitudes noted in Sect. 3.1.

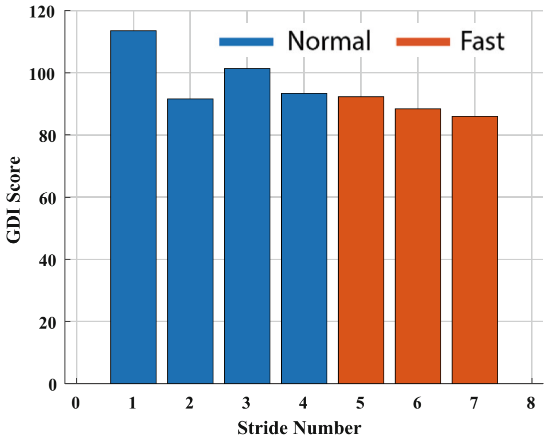

Fig. 3. Gait Deviation Index (GDI) scores for normal and fast strides. Control strides maintain high GDI scores indicating minimal deviation, while experimental strides show progressively lower scores, reflecting greater deviations from the normal flexion-extension pattern during fast walking.

Overall, GDI analysis quantitatively confirmed that fast walking introduced shifts in the timing of flexion peaks, while decreasing the variability between each stride compared to the flexion signatures of normal walking.

4 Discussion

This study evaluated the ability of the Gait Deviation Index (GDI) to quantify deviations in tibiofemoral flexion angle patterns induced by changes in walking speed. The flexion-extension curves demonstrated that Fast walking introduced consistent shifts in kinematics, including higher flexion angles at heel strike and pre-swing phases, earlier initiation of terminal swing, and a shortened foot-flat region. Although the overall structure of the gait cycle was maintained, amplitude and phase shifts became apparent when walking speed increased.

Singular Value Decomposition (SVD) of the control strides revealed that normal walking patterns could be accurately captured using a reduced number of modes, consistent with prior literature describing the highly structured nature of human gait. Deviations from these dominant control patterns were quantified using GDI. Experimental strides recorded during fast walking consistently exhibited lower GDI scores compared to control strides, indicating greater deviation from the normative gait feature space. Several experimental strides fell below the clinical threshold of 90, suggesting that increased walking speed introduced deviations that were both statistically and potentially clinically meaningful.

The lower GDI scores observed during fast walking reflect both phase shifts and amplitude differences. Such differences include earlier transitions into swing phase and elevated flexion at key gait events. These findings highlight that even within a healthy subject, systematic kinematic adjustments occur with changes in walking speed, which can be sensitively captured using SVD-based methods. While the general motion sequence of the gait cycle remained intact, these deviations could represent adaptations to maintain dynamic stability and propulsion efficiency at higher speeds.

A key strength of the present analysis is the ability to distinguish consistent kinematic adaptations from random stride-to-stride variability. Despite deviations, experimental strides remained internally consistent, as evidenced by the structured nature of the flexion profiles.

5 Future Work

The findings of this study open several avenues for future research to enhance the utility and applicability of SVD-based gait analysis in both clinical and research settings. While the present study focused on deviations induced by changes in walking speed in a healthy adult, future work should expand the subject pool to include a more diverse population in terms of age, body morphology, and physical condition. Most importantly, extending the analysis to individuals with gait pathologies, such as cerebral palsy, spinal cord injuries, or post-stroke impairments would allow the methodology to be validated in clinical contexts, similar to efforts made in deriving GDI adaptations for specific populations [2].

Further research should explore the contribution of higher-order modes beyond the first few dominant patterns, especially in pathological or compensatory gait conditions. While the first mode captures the global structure of flexion-extension movement, higher modes may reveal subtle deviations tied to specific events such as late stance deficiencies or swing phase abnormalities. Investigating the clinical interpretation of these modes and their correlation with rehabilitation outcomes could enhance the biomechanical relevance of SVD-based decompositions, as suggested in multi-mode analysis frameworks [2, 7].

In addition, integrating multi-modal gait data including electromyography (EMG), ground reaction forces, or metabolic energy expenditure, could provide a more comprehensive picture of neuromuscular control strategies. Combining SVD-based kinematic decomposition with techniques such as non-negative matrix factorization (NMF) or independent component analysis (ICA) for muscle synergy extraction could further contextualize observed deviations, as demonstrated in synergy-focused research [8].

From a methodological standpoint, exploring alternative or complementary dimensionality reduction techniques such as tensor decompositions, sparse principal component analysis (PCA), or hybrid SVD-ICA models, could improve the interpretability and robustness of gait pattern extraction [8, 9]. Such techniques may help isolate sources of variation that are not fully captured by the current SVD model, particularly in noisy or high-dimensional datasets.

By pursuing these future directions, the SVD-based GDI framework could evolve into a more comprehensive and clinically meaningful tool for understanding both healthy and pathological gait dynamics.

6 Conclusion

This work evaluated the impact of walking speed on tibiofemoral flexion-extension patterns using a Singular Value Decomposition (SVD)-based Gait Deviation Index (GDI) framework. Flexion angle profiles demonstrated that while the overall structure of the gait cycle was preserved under fast walking conditions, systematic amplitude and timing shifts occurred, including elevated initial flexion angles and earlier transitions into terminal swing. Quantitative analysis through GDI revealed that fast walking induced measurable deviations from the normative control pattern, with several strides exhibiting GDI scores below the 90-point threshold indicative of clinically meaningful gait deviation. These findings highlight the sensitivity of SVD-based GDI to both phase and structural changes in gait and demonstrate its utility for detecting even subtle adaptations in healthy gait under altered walking conditions.

References

1. Schwartz, M.H., Rozumalski, A.: The gait deviation index: a new comprehensive index of gait pathology. Gait Posture **28**(3), 351–357 (2008). https://doi.org/10.1016/j.gaitpost.2008.05.001
2. Guzelbulut, C., Suzuki, K., Shimono, S.: Singular value decomposition-based gait characterization. Heliyon **8**(12), e12006 (2022). https://doi.org/10.1016/j.heliyon.2022.e12006
3. Herrera-Valenzuela, D., Sinovas-Alonso, I., Moreno, J.C., Gil-Agudo, Á., del-Ama, A.J.: Derivation of the gait deviation index for spinal cord injury. Front. Bioeng. Biotechnol. (2022). https://doi.org/10.3389/fbioe.2022.874074

4. Grood, E.S., Suntay, W.J.: A joint coordinate system for the clinical description of three-dimensional motions: application to the knee. J. Biomech. Eng. **105**(2), 136–144 (1983). https://doi.org/10.1115/1.3138397
5. Caruntu, D.I., Hefzy, M.S.: 3-D anatomically based dynamic modeling of the human knee to include tibio-femoral and patello-femoral joints. ASME J. Biomech. Eng. **126**(1), 44–53 (2004)
6. Dabirrahmani, D., Hogg, M., Smith, P.N., Bryant, A.L., Lloyd, D.G.: Modification of the grood and suntay joint coordinate system to improve description of the knee joint motion. J. Biomech. **88**, 120–125 (2019). https://doi.org/10.1016/j.jbiomech.2019.03.022
7. Das, S.R., Wilson, R.C., Lazarewicz, M.T., Finkel, L.H.: Two-stage PCA extracts spatiotemporal features for gait recognition. J. Multimed. **1**, 9–17 (2006)
8. Tresch, M.C., Jarc, V.C., Kiehn, T.C.: Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets. J. Neurophysiol. **95**(4), 2199–2212 (2006). https://doi.org/10.1152/jn.00222.2005
9. Khan, H., Naseer, N., Yazidi, A., Kristian Eide, P., Wajahat Hassan, H., Mirtaheri, P.: Analysis of Human Gait Using Hybrid EEG-fNIRS-Based BCI System: A Review. Front. Human Neurosci. (2021). https://doi.org/10.3389/fnhum.2020.613254