Effects of Environmental Perturbations on Multijoint Gait Dynamics: A Multidimensional Recurrence Quantification Approach

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Abstract. Quantitative characterization of gait variability and stability is commonly used in the analysis of human locomotion. Multidimensional Recurrence Quantification Analysis is a recurrence-based approach that operates directly on multivariate time series and does not require reconstruction of phase space through time-delay embedding. The primary objective of this study was to determine and compare the values of Multidimensional Recurrence Quantification Analysis measures derived from gait data representing sagittal-plane joint angles of the lower limbs and pelvis. Data were recorded in the CAREN Extended environment under two experimental conditions: unperturbed gait and gait with externally induced mechanical perturbations. The study group consisted of fourteen young women. Statistical analyses were performed on the computed Multidimensional Recurrence Quantification Analysis measures, including an evaluation of effect sizes for the observed differences. The results demonstrated that Multidimensional Recurrence Quantification Analysis effectively distinguishes natural gait patterns from gait subjected to externally induced mechanical perturbations.

Keywords: human gait analysis, recurrence plot, Multidimensional Recurrence Quantification Analysis, CAREN Extended system

1 Introduction

Human gait is a dynamically adaptive process that depends on the continuous interaction between the neuromuscular system, sensory feedback, and the physical environment. Under steady and predictable conditions, gait exhibits stable yet flexible patterns that allow for efficient movement while maintaining balance. However, when unexpected disturbances occur, individuals must rapidly reorganize their movement strategies – modify joint coordination, increase attentional control, or adopt

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compensatory stabilization strategies – to preserve stability and prevent loss of balance. Consequently, the gait dynamics change under such perturbations.

Recurrence plots (RPs), introduced by Eckmann et al. [1], and recurrence quantification analysis (RQA), developed by Zbilut and Webber [2], are important tools for examining structure, regularity, and coordination patterns in biomechanical time series. RQA measures quantify the temporal organization of movement patterns in terms of determinism, laminarity, and entropy. Recurrence plots together with RQA have found application, among others, in the evaluation of the postural instability in PD patients [3] (PD stands for Parkinson's disease), in the assessment of assisted rehabilitation exercises maintaining mobility of the hip in case of coxarthrosis [4] as well as in the analysis of the heart rate variability [5-7], first of all with the purpose of cardiac arrhythmia detection. The multidimensional extension of RQA (MdRQA) introduced by Wallot et al. [8] and Wallot & Leonardi [9] is particularly well suited for analyzing multi-joint or multi-sensor data because it evaluates the evolution of the system in a multidimensional state space rather than treating individual signals independently.

The present study aimed to compare multidimensional gait dynamics across two walking conditions: a natural, stable walking scenario and a perturbed condition that introduces small, safe, but systematic disturbances to the walking surface. By applying MdRQA to multi-joint kinematic data, the authors investigate how perturbations alter the stability, regularity, and structural characteristics of gait, and to what extent recurrence-based measures can distinguish time series of human gait recorded under natural conditions from those obtained in the presence of external disturbances.

The paper is organized as follows: after the introduction (Section 1), Section 2 provides examples of MdRQA application. Section 3 describes the MdRQA measures used in the study and outlines the entire computational procedure. Section 4 details the experimental environment, the implemented scenarios, and the characteristics of the research group. Finally, Section 5 summarizes the findings and offers concluding remarks.

2 Related Work

Early research on recurrence methods in biomedical and movement science predominantly used univariate Recurrence Quantification Analysis or Cross-Recurrence Quantification Analysis (CRQA) [2,5,6,10]. In the foundational paper [8], MdRQA was demonstrated in research on joint and collective action using data from a study on teamwork that investigated the role of team emotions in cooperation [11].

In motor development (progressive acquisition, refinement, and organization of movement abilities), MdRQA has been used with wearable motion data to track how the complexity of infants' arm and leg movements evolves across the first year of life and across tasks [12].

In a perception-action phasing paradigm, MdRQA revealed tempo-dependent coupling patterns between human tapping and a metronome, differentiating successful from unsuccessful phasing strategies [13].

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MdRQA has also been applied to multichannel physiological synchrony in naturalistic group settings. In a collective decision-making task, interpersonal heart rate synchrony quantified using MdRQA, combined with machine learning analysis, predicted the likelihood of groups reaching the correct consensus more accurately than discussion duration, subjective team-function ratings, or heart rate measures alone [14].

It is worth noting that several methods papers [8,9] have consolidated best practices and reproducible workflows for applying MdRQA to multivariate behavioral and physiological time series (e.g., code and step-by-step procedures in R or MATLAB).

3 Methods

The state at time t is the vector X of all k variables measured at that moment:

$$X(t) = [x_1(t), x_2(t), \dots, x_k(t)] \,. \tag{1}$$

A recurrence plot illustrates the recurrence of states in a state space based on a binary symmetric square matrix in which element R_{ij} (a recurrence point) is defined as follows:

$$R_{ij} = \begin{cases} 1 & \|X_i - X_j\| \leq \varepsilon \\ 0 & \|X_i - X_j\| > \varepsilon \end{cases}, \tag{2}$$

where $\| \cdot \|$ denotes a norm (e.g., the Euclidean norm) and the parameter $\varepsilon, \varepsilon \geq 0$, is called the recurrence threshold. In other words, a value of 1 is assigned to the element R_{ij} whenever a point X_i on the trajectory is close enough to another point X_j [10]. Thus, a trajectory in a multidimensional state space can be analyzed using a two-dimensional representation of its recurrences.

‘Classical’ Recurrence Quantification Analysis and Multidimensional RQA rely on the same recurrence plot formalism, but differ fundamentally in how the state space is defined. Classical RQA reconstructs it from a single time series using time-delay embedding and quantifies recurrence patterns in the reconstructed dynamics of the observed variable. In contrast, MdRQA operates directly on multivariate signals, i.e., without embedding, constructing the state space from multiple simultaneously measured variables, such as pelvic tilt and hip, knee, and ankle angles, and treating the multijoint configuration as a single evolving dynamical system.

To quantify RP features, both RQA and MdRQA use the same set of measures based on diagonal and vertical line structures in recurrence plots. Diagonal structures reflect repeated, predictable evolution of the system over time, whereas vertical structures represent periods during which the system remains in the same region of state space.

Recurrence rate (RR) is the density of recurrence points in an RP:

$$RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{ij} \,, \tag{3}$$

where N denotes the number of time points in the analyzed signals (that are of equal length).

Determinism (DET) is the proportion of recurrence points that form diagonal lines:

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$$DET = \frac{\sum_{l=l_{min}}^{l_{max}} l \cdot P(l)}{\sum_{i,j=1}^{N} R_{ij}}. \tag{4}$$

where $P(l)$ is the number of diagonal lines of length l. If L_{min} denotes the minimum length of such lines ($L_{min} = 2$), and L_{max} is the length of the longest diagonal line, excluding the main diagonal ("the line of identity"), then the average length of diagonal lines (L_{mean}) is calculated in the following way:

$$L_{mean} = \frac{\sum_{l=L_{min}}^{L_{max}} l \cdot P(l)}{\sum_{l=L_{min}}^{L_{max}} P(l)}. \tag{5}$$

The denominator in formula (5) represents the total number of diagonals. L_{mean} is an estimation of the average time interval during which two segments of the trajectory are close to each other.

Shannon entropy of the frequency distribution of the diagonal lines' lengths (ENTR) is described by the following formula, known from the theory of information

$$ENTR = -\sum_{l=l_{min}}^{l_{max}} p(l) \cdot \ln p(l), \tag{6}$$

with frequency distribution $p(l)$ defined as follows:

$$p(l) = \frac{P(l)}{\sum_{l=L_{min}}^{L_{max}} P(l)}. \tag{7}$$

ENTR reaches its maximum for the uniform frequency distribution. Consequently, higher ENTR values indicate periodic behavior of the system, lower values result from chaotic behavior, and values close to 0 are typical of noise.

Measures for vertical lines are defined analogously to their counterparts for diagonal lines. Laminarity (LAM) is the proportion of recurrence points that form vertical lines:

$$LAM = \frac{\sum_{v=V_{min}}^{V_{max}} v \cdot P(v)}{\sum_{i,j=1}^{N} R_{ij}}. \tag{8}$$

TT ("trapping time") is the average length of vertical lines. It represents the average duration for which the system remains "trapped" in a similar dynamical state.

$$TT = \frac{\sum_{v=V_{min}}^{V_{max}} v \cdot P(v)}{\sum_{v=V_{min}}^{V_{max}} P(v)}, \tag{9}$$

where $P(v)$ is the number of vertical lines of length v. The denominator in formula (9) represents the total number of such lines. V_{min} and V_{max} denote the minimum and the maximum length of vertical lines, respectively ($V_{min} = 2$).

Some preparatory work is required before calculating MdRQA measures. To suppress trivial short-lag recurrences caused by temporal autocorrelation in the time series, a Theiler window, which masks a symmetric band of samples around the line of identity, should be applied in the recurrence plot. This exclusion prevents points that are adjacent in time, but not dynamically informative, from contributing to the recurrence structure.

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All kinematic signals should be z-score standardized (zero mean, unit variance) to ensure that each variable contributes equally. This step prevents the Euclidean distance metric, used to construct the recurrence plot, from being dominated by joints with larger numerical ranges or higher variance.

To reduce dimensionality and avoid collinearity among the joint angle signals, the Principal Component Analysis (PCA) should be applied to the standardized multichannel kinematic data prior to recurrence analysis. PCA transforms the original, correlated joint trajectories into an orthogonal coordinate system and orders the new axes by descending explained variance. The first three principal components, which capture the dominant modes of lower limb movement, determine the three-dimensional trajectory that served as the state space for the MdRQA.

A critical methodological consideration in RQA and MdRQA concerns the selection of the recurrence threshold ε. Because ε determines which states in the reconstructed state space are considered recurrent, its choice has a direct impact on the interpretability and stability of recurrence measures. Several alternative "rules of thumb" have been proposed for determining ε [15,16]: a value which should not exceed 10% of the mean or the maximum state space diameter, or a value that guarantees a density of recurrence points (RR) of approximately 1%.

For each trial, the following steps must be performed:

1. Data acquisition (seven joint-angle channels**).**
2. Preprocessing of raw kinematic signals (e.g., trim all signals to an equal length by removing initial zeros).
3. Apply z-score standardization to each signal.
4. Perform the dimensionality reduction (Principal Component Analysis).
5. Construct the multivariate state-space trajectory from the principal components.
6. Select the recurrence threshold ε.
7. Construct the recurrence plot, apply a Theiler window.
8. Compute MdRQA measures.

4 Experiments and Results

The data used for the calculations were recorded using the Vicon motion capture system, which is a component of the CAREN Extended environment by Motek [17] (Fig. 1). The CAREN Extended (Computer Assisted Rehabilitation Environment) system comprises a large immersive dome equipped with a dual belt instrumented treadmill mounted on a six degrees of freedom motion platform (movements: forward/backward, up/down, left/right). During each trial, the participant walks in a safety harness while wearing a motion capture suit with reflective markers placed on key anatomical landmarks. A network of infrared cameras records the 3D trajectories of all markers, and the system reconstructs their coordinates over time to generate a full kinematic representation of the movement. These data are mapped onto a skeletal model, enabling the computation of joint angles and other biomechanical variables for further analysis. The virtual environment is enhanced with surround sound and dynamic visual projections, providing the exercising participant with an immersive and realistic

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walking experience. Motion capture recordings are stored in standard C3D format for subsequent processing.

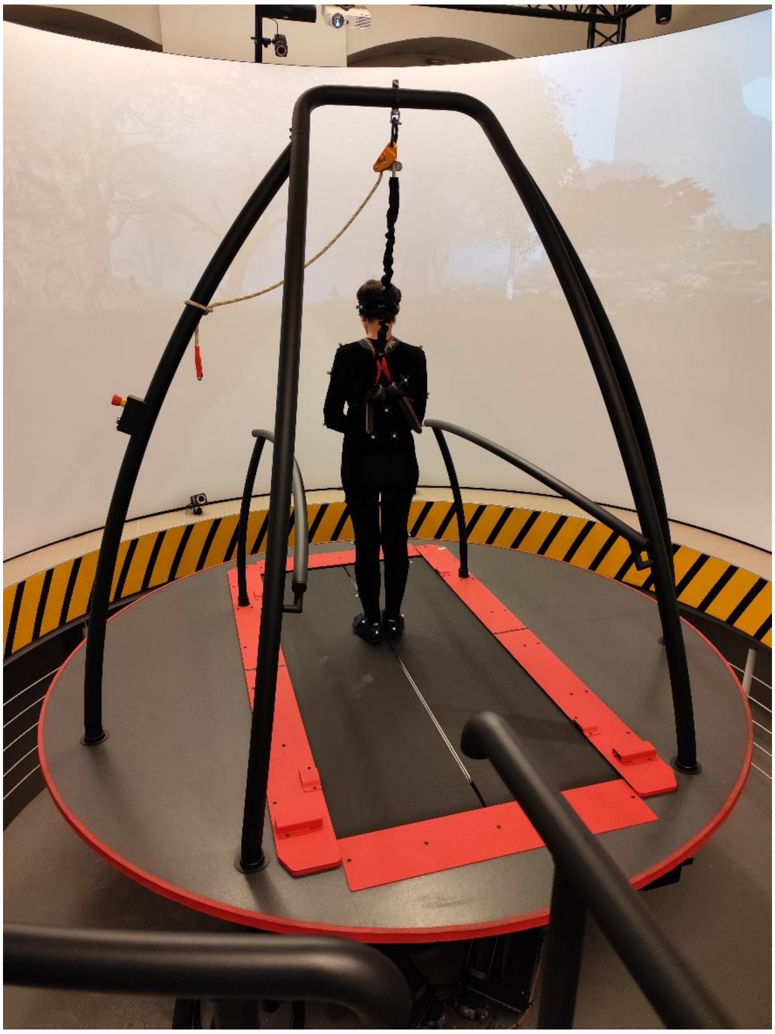

Fig. 1. A subject performing an exercise in the CAREN Extended environment.

14 female PhD students from Silesian University of Technology participated in experiments that were carried out according to the following scenarios, combining all the advantages of the CAREN Extended system:

- ‘forest walking’ – normal gait through a forest with preferred walking speed (self-paced),
- ‘rope bridge’ – a participant views a narrow rope-bridge path suspended over turbulent water, while the motion platform delivers sudden, rapid side-to-side perturbations accompanied by howling-wind audio.

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The number of trials conducted within the individual experimental scenarios was 40 ('forest walking') and 39 ('rope bridge'). Each trial lasted approximately 1 minute, and data were recorded at 100 Hz, finally producing a set of ca. 6000-point time series.

The analysis focused on movements in the sagittal plane, which predominates during gait. Specifically, pelvic motion and the movements of three lower limb joints (hip, knee, and ankle) were examined. It is worth noting that the lower limb kinematic chain naturally maps onto the multidimensional state space used by MdRQA, although dimensionality reduction is suggested to avoid redundancy among highly correlated degrees of freedom.

Time series data were obtained from the Vicon motion capture system for pelvic tilt, hip and knee flexion/extension angles, and ankle dorsiflexion/plantarflexion. Pelvic tilt describes the upward or downward inclination of the pelvis in the sagittal plane. Hip flexion/extension refers to the forward and backward movement of the thigh relative to the pelvis. Knee flexion/extension denotes the bending and straightening movement of the shank relative to the thigh. Ankle dorsiflexion/plantarflexion describes the upward movement of the foot toward the tibia (dorsiflexion) and the downward movement away from the tibia (plantarflexion).

Time series were aligned to trial onset and, when necessary, trimmed to equal duration. Each time series was z-scored within trial to prevent amplitude-dominated distance metrics in the state space. PCA was then applied to the standardized data, and the first three principal components, which captured the vast majority of the variance, were retained to define the multivariate trajectory used for MdRQA. The recurrence threshold ε was chosen to enforce a fixed recurrence rate of $RR = 1\%$. A Theiler window of 40 samples (400 ms) was applied symmetrically around the line of identity to remove trivial short-lag recurrences. Finally, MdRQA measures (DET, L_{max}, L_{mean}, ENTR, LAM, V_{max}, and TT) were computed in MATLAB. Figures 2 and 3 present exemplary recurrence plots for both experimental scenarios.

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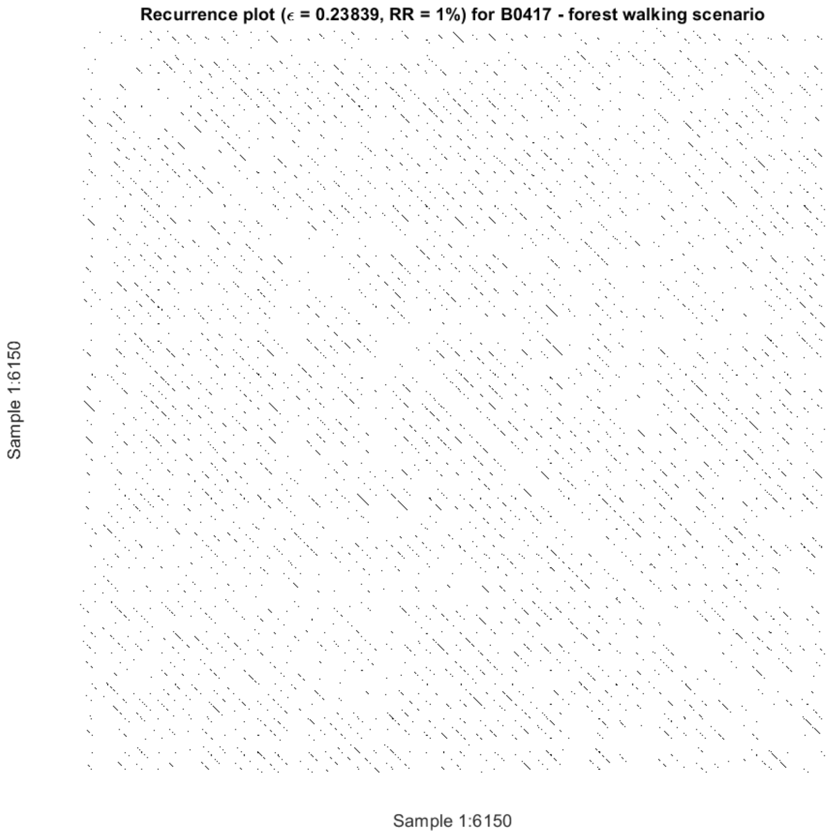

Fig. 2. Exemplary recurrence plot for the ‘forest walking’ scenario.

The forest walking plot exhibits a uniform, almost continuous diagonal texture extending across the entire plot. The diagonals are long, densely packed, and only minimally interrupted, indicating a repeatable, cyclic gait pattern with consistent inter-joint coordination across consecutive cycles. Vertical structures are very sparse, suggesting a smooth progression through the gait phases without prolonged dwell time in specific joint configurations. In addition, a clearly visible Theiler window surrounding the main diagonal reflected the intentional exclusion of trivial recurrences at short temporal distances.

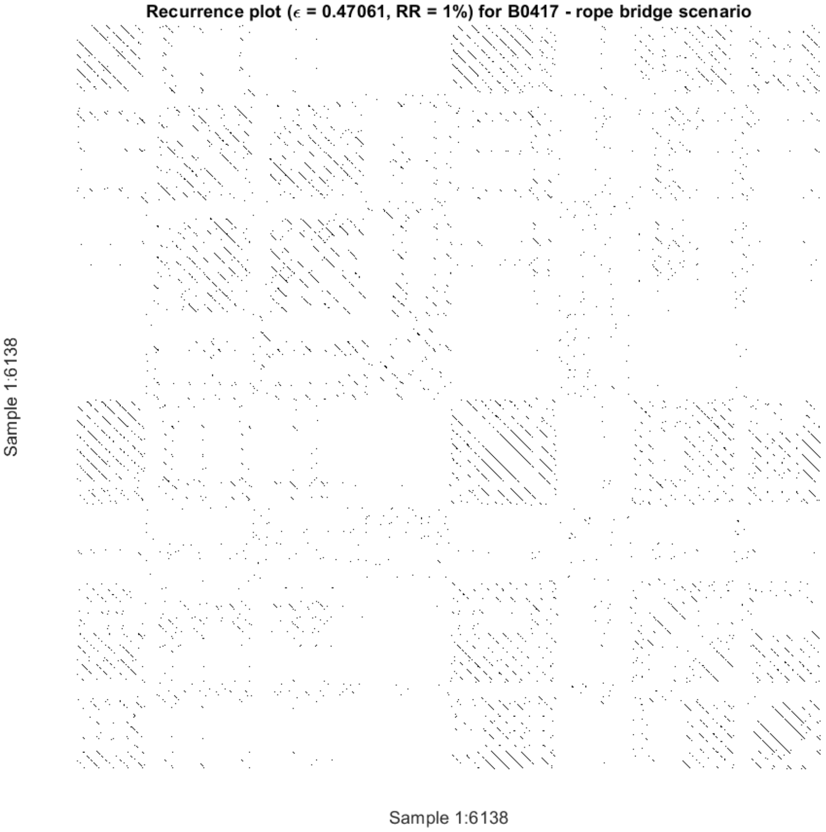

Fig. 3. Exemplary recurrence plot for the 'rope bridge' scenario.

During rope bridge walking, the recurrence structure appears segmented, forming distinct blocks of diagonal patterns separated by regions of low recurrence density. Diagonal lines are present but intermittent, indicating periods of locally repeatable coordination. Several clusters of short vertical structures are also visible, reflecting brief trapping episodes in which the joint configuration of the lower limbs lingers in similar states for stabilization.

Each pair of boxplots in Fig. 4 illustrates the distribution, central tendency, and variability of a given MdRQA measure across trials conducted under two experimental scenarios. The boxplot for RR results directly from the assumption of a fixed recurrence rate during recurrence plot construction. For this reason, this measure was not included in the statistical analysis.

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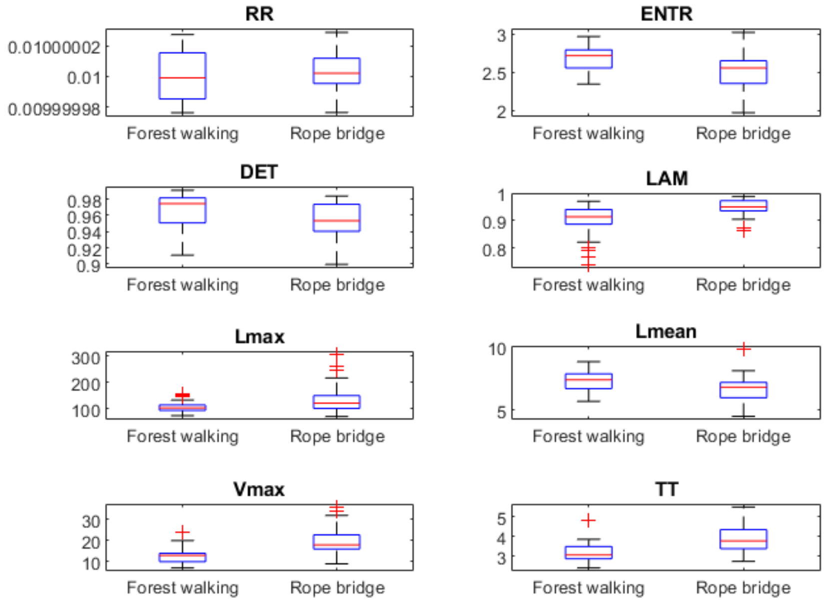

Fig. 4. Boxplots of all MdRQA measures for the ‘forest walking’ and ‘rope bridge’ scenarios.

The statistical analysis was performed in several steps. For each MdRQA measure, the distribution's normality was first assessed using the Shapiro-Wilk test at the significance level $\alpha = 0.05$. Because normality was violated for several measures (3 of 7) in both scenarios, and to maintain a consistent analysis across outcomes, group differences between ‘forest walking’ and ‘rope bridge’ scenarios were assessed using the two-sided Mann-Whitney U test (Wilcoxon rank-sum; $\alpha = 0.05$). Alongside p-values, the rank-biserial correlation was computed as an effect-size measure. To evaluate whether the variability of each metric differed between scenarios, Levene’s test based on absolute deviations from the median was applied. Multiple comparisons across the set of MdRQA measures were controlled using the Benjamini-Hochberg false-discovery-rate (FDR) procedure with FDR-threshold $q = 0.05$ (i.e., no more than 5% of significant findings are expected to be false discoveries). Although multiple trials were recorded from each participant, the analysis was conducted at the trial level, treating each trial as an independent realization of the experimental condition, while subject-level dependencies are acknowledged as a limitation of the current statistical approach. The results of the statistical analysis are presented in Table 1.

Table 1. Mann-Whitney U test, Levene's test, and effect size results.

Measure	p-value (U test)	Significance (U test)	Effect size	p-value (Levene test)	Significance (Levene test)
DET	0.011	significant	small	0.989	
Lmax	0.003	significant	medium	< 0.001	significant
Lmean	0.005	significant	small	0.175	
ENTR	< 0.001	significant	small	0.099	
LAM	< 0.001	significant	large	0.005	significant
Vmax	< 0.001	significant	large	0.014	significant
TT	< 0.001	significant	large	0.040	significant

The boxplots and statistical analyses indicate biomechanical differences between natural walking and mechanically perturbed walking. Perturbed gait was characterized by increased laminarity (LAM), trapping time (TT), and maximum vertical line length (V_{max}), reflecting more frequent and prolonged stabilization phases, with several of these measures exhibiting large effect sizes. In contrast, diagonal-based measures such as L_{max}, L_{mean}, determinism (DET), and entropy (ENTR) were reduced, indicating decreased stride-to-stride predictability and altered inter-joint coordination. Together, these findings indicate systematic alterations in gait dynamics associated with externally induced mechanical perturbations, toward more adaptive and cautious locomotor control. This interpretation is further supported by Levene test results, which revealed increased variance in several measures under perturbed conditions.

5 Conclusions

This study examined how human gait dynamics adapt to a destabilizing environment using Multidimensional Recurrence Quantification Analysis. While MdRQA is an established analytical framework, this study shows that it is sensitive to externally induced gait perturbations in an immersive CAREN Extended system. Recurrence plots were constructed with a fixed recurrence rate to ensure comparability across measures, and group differences were tested using two-sided Mann-Whitney U tests with rank-biserial correlation. The MdRQA measures revealed significant differences across the experimental scenarios. The results indicate that MdRQA clearly distinguishes natural gait from gait subjected to externally induced mechanical perturbations.

A methodological advantage of MdRQA is that it operates directly within the multidimensional state space defined by the recorded signals, eliminating the need to reconstruct the phase space from a single scalar time series and to search for time delay and embedding dimension parameters. Moreover, MdRQA treats all channels symmetrically, although proper channel standardization and careful selection of the recurrence threshold ε remain essential to ensure meaningful and comparable results.

From a rehabilitation perspective, the observed sensitivity of MdRQA measures to externally induced gait perturbations suggests that this approach could be applied to monitor changes in locomotor control during training or therapeutic interventions

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aimed at improving gait stability. Further research is required to confirm its usefulness in clinical populations.

In summary, the results indicate that MdRQA can detect changes in gait dynamics caused by mechanical perturbations. Future work may extend this study by incorporating other RQA-based variants, including diagonal cross-recurrence profiles (DCRP) and multidimensional cross-recurrence analysis (MdCRQA), and by integrating these methods with machine learning pipelines for automated detection and classification of altered gait dynamics.

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