Performance Evaluation of Gait Classification Using Quaternion Waveforms

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Abstract

Visual gait assessment in physical therapy is subjective and may lack accuracy. Three-dimensional motion analysis is precise, but it is expensive and difficult to use in daily clinical settings. This study examined whether abnormal gait patterns can be analyzed using quaternion time-series data obtained from a single smartphone-based inertial measurement unit (IMU). Nineteen healthy adults performed normal walking and four types of simulated abnormal gait. A smartphone was fixed at the waist, and gait data were recorded during a 10 m walk. Gait cycles were extracted and normalized to 100 points. The four quaternion components were analyzed as multivariate time-series data over one gait cycle. Principal component analysis and clustering showed differences in waveform structure between gait patterns. Clear separation was observed between normal gait and Trendelenburg gait. A support vector machine classifier achieved an accuracy of 0.83 and a Macro-F1 score of 0.84 using cross-validation. When leave-one-subject-out validation was applied, classification performance decreased. This result suggests that individual differences and waveform variability influence gait classification. These findings indicate that quaternion time-series data obtained from a single smartphone IMU can capture structural characteristics of gait patterns. This approach may support objective and practical gait analysis in physical therapy.

Keywords: Quaternion; Gait classification; Smartphone sensors; IMU; PCA

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1 Introduction

In physical therapy, gait analysis is important for evaluating physical function and making treatment plans. Especially in people with diseases or disabilities, specific movement patterns often appear during walking. Accurate evaluation requires not only visual observation but also analytical and quantitative viewpoints. Reference [21] reported that although observational gait analysis is commonly used in clinical practice, there are problems with reliability, validity, and differences between examiners. In addition, Reference [13] showed that in a national survey, more than 70% of physical therapists felt difficulty in gait analysis, partly because of low observational accuracy. Therefore, although gait observation is essential for physical therapists, it is affected by individual experience and skill, and there are also problems in education [13] . To support this subjective evaluation, some studies have proposed combining observation with quantitative measurements, such as three-dimensional treadmill analysis or video-based evaluation [15]. These studies show the importance of recording and evaluating movement objectively and indicate that quantitative approaches to gait analysis are becoming increasingly necessary.

Traditionally, three-dimensional motion analysis systems and accelerometers have been used for quantitative evaluation of gait. Three-dimensional motion analysis provides detailed visualization of joint motion, but it is limited by space and measurement conditions, which makes it difficult to use in clinical settings [18]. Accelerometers are inexpensive and portable, and they are useful for detecting linear movements. However, it is difficult to accurately evaluate complex movements such as pelvic rotation or trunk tilt, and problems remain in distinguishing such movements [9, 22]. Recently, camera-based pose estimation technology has expanded the options for motion analysis. Still, there are problems such as sensitivity to camera angles, occlusion, recognition errors depending on participant distance, and restrictions on the environment [19]. Therefore, methods that can handle both practical use in the field and complex motion are required.

In this context, the use of inertial measurement units (IMU), which include acceleration, angular velocity, and geomagnetic sensors, has received increasing attention. Although small in size, IMU can record body motion in three-dimensional space. They are now widely used as common measurement devices and are also built into smartphones. In particular, the method that estimates posture from acceleration, angular velocity, and geomagnetic data using quaternions [11] allows smooth reproduction of sensor motion and orientation. This improves the accuracy of motion analysis with IMU. Recent studies have also compared IMU with optical motion capture systems and confirmed their reliability, showing potential for clinical use [16]. These advances in algorithms have made it possible to visualize complex movements such as postural inclination and pelvic rotation more precisely. As a result, IMU are useful for detecting small movements of the pelvis and trunk that are often missed by conventional methods.

Recent studies have shown that gait analysis using IMU and quaternions is effective. Reference [20] reported that processing accelerometer and gyroscope data with quaternions enables accurate measurement of three-dimensional movements of the hip and knee joints. Reference [17] proposed a method for estimating posture during motion by continuously processing rotational data from sensors and showed that quaternion-based calculations are suitable for smooth tracking of rotation. In addition, Reference [14] indicated that aligning the IMU with the body coordinate system improves the accuracy of joint angle estimation, and that using quaternions allows smooth reproduction of joint motion. These studies suggest that IMU analysis using quaternions is a reliable method for quantitatively capturing complex body movements.

However, most previous studies have focused on normal gait in healthy individuals, and the characteristics of abnormal gait have not been well examined. Movements such as pelvic rotation and tilt are also difficult to observe visually, and it is challenging to detect changes such as lateral asymmetry or timing variation in abnormal gait. Quantifying small deviations, rhythm disturbances, and uneven directional movements as continuous waveforms is important as a basic step for future clinical use.

In this study, quaternion waveform data obtained during walking were analyzed. The aim was to describe abnormal gait as quantitative features based on time-series changes that reflect pelvic rotation and tilt. Specifically, this study examined how accurately multiple abnormal gait patterns can be automatically identified using quaternion waveforms from smartphone-based IMU. In addition, waveform changes were visualized to reveal differences and characteristics between gait patterns. Through these analyses, the study aimed to clarify how the structural features contained in quaternion waveforms affect the identification and classification of abnormal movements. This approach may also help beginners who have difficulty making judgments and individuals who are unaware of their own movement changes. It is expected to provide a foundation for improving the quality of physical support and assistance.

2 Related literature

2.1 Studies Using Accelerometers in Physical Therapy

In the field of physical therapy, many studies have used accelerometers to evaluate gait and postural stability objectively. Accelerometers are inexpensive, easy to handle, and can be easily applied in clinical settings. Therefore, they are widely used for quantitative assessment of gait and movement and for understanding physical function. Reference [12] organized methods for quantitatively evaluating stability and fall risk by analyzing trunk acceleration during posture and gait. It showed that variations in trunk acceleration in the anterior-posterior and vertical directions reflect postural control ability, suggesting that acceleration analysis can support balance evaluation and fall prediction in clinical practice. Reference [7] also showed that analyzing acceleration waveforms from sensors attached to the trunk and lower limbs allows evaluation of gait stability and symmetry. These studies suggest that accelerometers are effective for quantitatively extracting gait waveform features and for objectively assessing gait abnormalities.

Analysis using acceleration signals during walking has expanded to capture movement characteristics more comprehensively by changing the measurement site, such as the trunk or lower limbs. Reference [8] verified the accuracy of gait measurement using acceleration sensors attached to the lower limbs in stroke patients and reported that the accuracy depends on the attachment site. Reference [3] reviewed the application of wearable sensor technology for evaluating gait, balance, and joint range of motion and confirmed its effectiveness in clinical evaluation. These studies show that accelerometers are useful for numerically evaluating trunk and lower limb movements.

In recent years, accelerometers have also been applied to the evaluation of activities of daily living (ADL) and physical activity levels. Reference [10] reported that among elderly people, those with higher physical activity levels measured by accelerometers showed better subjective health and physical function. This suggests that accelerometers can be used for preventive care and for assessing activity levels.

Therefore, in the field of physical therapy, quantitative evaluation using accelerometers has been developed and applied not only to gait analysis in clinical practice but also to broader assessments of physical activity.

2.2 Studies Using IMUs

Accelerometers are effective for capturing the magnitude and direction of motion, but it is difficult to evaluate three-dimensional postural changes such as body rotation and tilt. In recent years, inertial measurement units (IMU), which integrate acceleration and angular velocity, have been developed to enable higher-precision motion analysis.

Reference [2] verified the validity and reliability of a gait analysis system using IMU and reported high agreement with a camera-based three-dimensional motion capture system. This result indicates that IMU can measure body movements in three dimensions with high precision and can provide more objective evaluation than visual observation. Reference [5] analyzed acceleration data obtained from nine-axis IMU sensors attached to the trunk and lower limbs of patients with knee osteoarthritis and healthy individuals. The study found a strong correlation between the power spectrum ratio of trunk acceleration and the knee flexion angle, showing that joint motion characteristics can be quantified from trunk acceleration alone. Reference [6] examined the accuracy of joint angle measurement using IMU sensors and confirmed high consistency with optical motion capture. It also reported that relative joint angle changes measured by IMU are accurate enough for clinical application, although absolute angles still show some error.

These studies show that IMU are useful tools for quantitatively capturing body motion in three dimensions. They serve as complementary technology to accelerometer-based analysis and are becoming increasingly applied in physical therapy for high-precision evaluation of gait and posture.

2.3 Studies Using Quaternions

Studies using quaternions have been reported as a method to capture rotational motion and attitude changes from sensor data with high precision and stability. Quaternions can avoid the problem of gimbal lock that occurs in attitude representation using Euler angles. When estimating orientation by integrating acceleration and angular velocity, quaternions are also less affected by rotation order and integration error, allowing stable estimation. Therefore, they are suitable for smoothly representing complex three-dimensional changes such as body rotation and tilt.

To improve pose estimation accuracy, Reference [4] developed an algorithm that combines quaternions with an extended Kalman filter and reported high-precision pose estimation with reduced noise. Reference [1] analyzed jump landing motions by converting IMU data into quaternions and showed that three-dimensional movement can be quantitatively evaluated with high reliability. Other studies have reported that quaternion decomposition enables accurate alignment between IMU sensors and the body coordinate system.

Although research using quaternions for gait and posture analysis is progressing, most studies have focused on improving posture estimation for normal gait or specific movements in healthy individuals. Few studies have analyzed the entire waveform structure as time-series data.

2.4 Positioning of This Study

In physical therapy, studies using accelerometers and IMU for gait and motion analysis have progressed, providing quantitative evaluation of physical function and gait stability. It has also been shown that quaternions can reproduce three-dimensional postural changes such as body rotation and tilt smoothly. However, most of these studies have focused on posture estimation or angle calculation at specific time points, and methods to analyze the entire movement as time-series data are not yet well established.

Accelerometers are mainly designed to detect linear acceleration and the direction of gravity, and they cannot directly measure rotational motion. Even when using IMU, integration errors and axis misalignment may cause differences between estimated and actual rotation. Considering these limitations, this study focuses on the structural features contained in quaternion waveform time-series and aims to understand gait motion in a more integrated and quantitative way.

3 Method

3.1 Overview of This Study

This study aimed to measure five types of simulated gait using sensors mounted on a smartphone and to extract the characteristics of each gait pattern from quaternion waveform data. The waveform data were preprocessed and analyzed to examine the distinctiveness of abnormal gait patterns. In this study, simulated abnormal gait performed by healthy participants was used instead of patient gait. This approach ensured experimental safety and reproducibility and aimed to confirm the effectiveness of quaternion-based gait classification before applying it to clinical cases. The following sections describe the participants, measurement conditions, data processing, and analysis methods. This study was approved by the Research Ethics Committee of the Faculty of Informatics, Kansai University (Approval No.: Kansai-Sou-Rin No. 2024-27).

3.2 Participants

This study included 19 healthy adults (7 males and 12 females, aged 20–22 years) who were students in a physical therapy training program. Participants were selected because they had no major orthopedic or neurological disorders, to ensure safe and consistent gait measurement under controlled conditions. All participants had basic education in physical therapy and understood the characteristics of abnormal gait commonly observed in clinical practice.

For each simulated gait pattern, a physical therapist explained and demonstrated the movements verbally and by example. Participants practiced these movements before measurement. Each trial was checked by the examiner based on clinical observation, and trials that were clearly inappropriate as simulated gait were excluded. Trials that reproduced the target gait characteristics were used for analysis.

3.3 Walking Conditions and Measurement Environment

Each participant performed a 10 m straight-line walk. The starting position was upright, and walking began with the right foot upon the participant's own signal. The walk ended after stopping with both feet together at about 10 m. Five gait patterns were measured: one normal gait pattern and four simulated abnormal patterns. The abnormal patterns simulated gait with weakened right hip abductor muscles, which are commonly observed in clinical settings (Figure 1).

In this study, each trial of the simulated abnormal gait was labeled by one physical therapist with clinical experience, based on predefined observation criteria. The criteria for each gait pattern were defined as follows. Trendelenburg gait was defined as a gait pattern in which a clear drop of the left pelvis was observed from the posterior view during the right stance phase. Circumduction gait was defined as a gait pattern in which, during the swing phase of the left lower limb, the limb was swung outward in an arc shape with hip abduction. Duchenne gait with hip abduction was defined as a gait pattern in which, during the right stance phase, the trunk leaned toward the right side, while the swinging left lower limb showed hip abduction at the same time. Duchenne gait without hip abduction was defined as a gait pattern in which, during the right stance phase, the trunk leaned toward the right side, while the swinging left lower limb did not show hip abduction. For all gait patterns, only trials in which the defined observations were consistently confirmed across multiple consecutive gait cycles were included in the analysis. As an

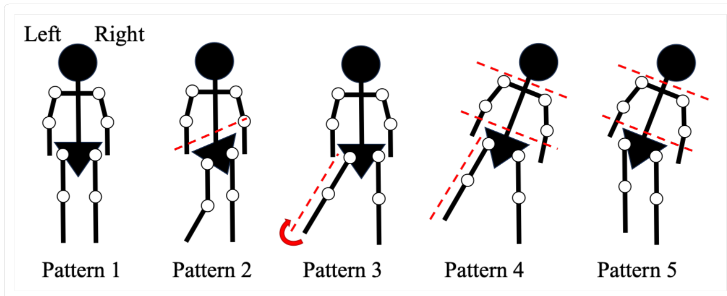

Figure 1: Simulated gait patterns. Pattern 1: normal gait, Pattern 2: Trendelenburg gait, Pattern 3: circumduction gait, Pattern 4: Duchenne gait (with hip abduction), Pattern 5: Duchenne gait (without hip abduction).

Figure 2: Smartphone attachment (posterior and lateral views)
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auxiliary validation of labeling, gait videos corresponding to the simulated abnormal gait conditions were independently reviewed by two physical therapists under blinded conditions. Inter-rater agreement was evaluated using Cohen's kappa, showing substantial agreement (K = 0.81). No trials were excluded or relabeled based on this auxiliary review. All analyses were conducted using the originally defined labels.

During walking, a smartphone (iPhone, iOS 17.4.1) was fixed to the lower back at the level of the iliac crests using a dedicated holder. The device was placed horizontally, with the charging port facing the right side. The smartphone was securely fixed to the lower back (Figure 2). In this study, the local coordinate system of the smartphone was used to define pelvic motion in three dimensions. The X-axis represented the vertical direction and horizontal rotation, the Y-axis represented sagittal tilt along the lateral axis, and the Z-axis represented flexion and extension along the anterior–posterior axis.

3.4 Data Acquisition and Sensor Specifications

A dedicated smartphone application was developed to collect gait motion data. The application enabled real-time recording of acceleration, angular velocity, and quaternion data (X, Y, Z, W). All data were stored in CSV format within the device. The recorded data were analyzed by dividing them into gait cycle units, referred to as "Segments," as described in the following section.

3.5 Extraction of Gait Cycles

Gait cycles were defined based on acceleration in the forward–backward direction (Z-axis) of the device coordinate system. The acceleration data were first converted from the device coordinate system to the global coordinate system using quaternion-based attitude correction. The positive peaks of the forward–backward component (corr_acc_X) were extracted as approximate indicators of heel contact.

Multiple gait cycles corresponding to odd steps (right–left–right) were extracted from stable intervals, excluding the first and last steps (e.g., 3rd–5th, 5th–7th, 7th–9th). The number of effective segments obtained from each gait pattern (Patterns 1-5) was 107, 142, 136, 144, and 155, respectively.

3.6 Data Processing and Analysis Methods

For each segment, preprocessing and analysis were performed on the quaternion waveform data of four axes (X, Y, Z, W). To correct for differences in the number of data points, linear interpolation was applied to each gait cycle, standardizing all to 100 points. Offset correction was then performed to remove the influence of initial values by aligning the first value of each axis to zero.

The preprocessed waveform data (100 points $\times$ 4 axes = 400 dimensions per segment) were analyzed using the following methods:

3.6.1 Z-score transformation

For each gait pattern, the mean and standard deviation were calculated for each segment. Time-series data were normalized using Z-scores, allowing comparison of variability within and between patterns on a unified scale. Based on the normalized data, clustering and visualization were conducted to identify differences between normal and abnormal gait.

3.6.2 Principal Component Analysis (PCA)

PCA was applied to each 400-dimensional segment to examine structural variation and the direction of fluctuation in the waveform. The variables consisted of 100 interpolated points for the four quaternion axes. Dimensionality reduction was performed without class labels to visualize the main sources of variation and distribution tendencies across patterns.

3.6.3 Clustering (K-means method)

K-means clustering (K = 5) was performed on the PCA principal component scores to explore structural similarities and separability of waveforms. The clustering analysis was intended as an auxiliary tool for waveform interpretation rather than as a data-driven unsupervised discovery of optimal cluster structures. Accordingly, the number of clusters was set to K = 5 to facilitate the interpretation of waveform characteristics in relation to the five predefined gait conditions. The Z-score waveforms belonging to each cluster were visualized to interpret multidimensional differences and common features between clusters. The focus was on identifying characteristic waveform trends rather than quantitatively evaluating separability or accuracy.

3.6.4 Classification model construction

To evaluate the distinguishability of each gait pattern, a Support Vector Machine (SVM) with a radial basis function (RBF) kernel was used. The RBF kernel was selected because the input features consisted of high-dimensional time-series data with potentially non-linear class boundaries under a limited sample size. All preprocessing steps and model-related procedures, including feature standardization and handling of SVM hyperparameters, were performed using only the training data in each validation split. Leave-One-Subject-Out (LOSO) cross-validation was primarily used to evaluate generalization performance across participants, ensuring that data from the same participant were not shared between training and test sets. In addition, 5-fold and repeated 5×10 cross-validation were conducted as supplementary analyses to examine the stability and reproducibility of classification performance under different data partitions. The input feature was the 400-dimensional vector after interpolation and correction. Recognition performance was evaluated by accuracy and F1 score.

Finally, when interpreting the Z-scores and clustering results, both quantitative and qualitative aspects—such as waveform shape, peak structure, and timing shifts—were examined to visualize structural differences in abnormal movements.

In this study, quaternion data were not used for strict rotation reconstruction or rotational computation. Instead, the four quaternion components (X, Y, Z, W) were treated as multivariate time-series signals representing changes in pelvic orientation during gait. Preprocessing such as interpolation, offset correction, and normalization was applied to each component to emphasize waveform structure and temporal patterns relevant to gait classification.

4 Result and Discussion

4.1 Presentation of Research Results

The waveform data of each gait pattern obtained from the above processing were analyzed to visualize variance structures using principal com-

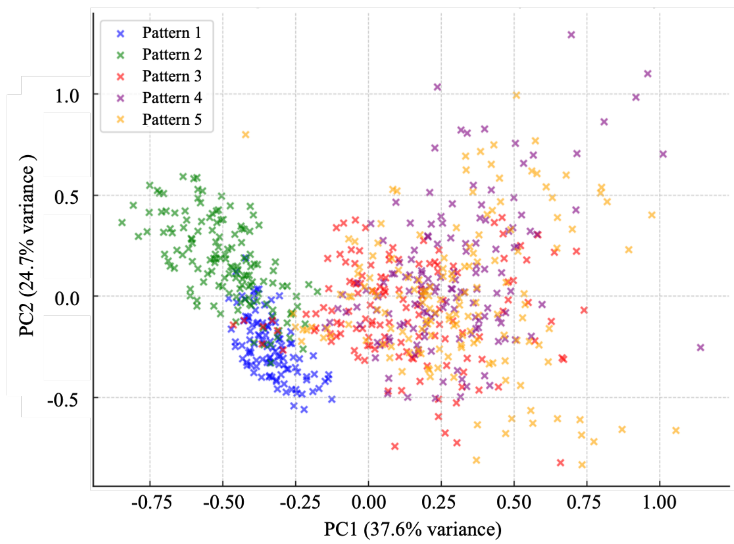

Figure 3: PCA plot of Quaternion Waveforms (PC1 vs. PC2)

ponent analysis (PCA), extract latent structures through clustering, and verify classification accuracy using a classification model. In the clustering results, representative waveforms for each cluster were plotted in Z-score format relative to Pattern 1, and qualitative differences were also examined. The following sections describe these results and discuss the characteristics and separability of each gait pattern.

4.1.1 Principal Component Analysis (PCA)

PCA was applied to the quaternion waveforms of each segment to visualize the overall fluctuation trends and distribution of the waveforms. The contribution ratios of the first and second principal components were 37.6% and 24.2%, respectively, with a cumulative contribution of 61.8% (Figure 3). The first and second components showed large contributions from the X- and Y-axes, suggesting that pelvic rotation and tilt are the main sources of waveform variation.

As shown in Figure 3, in PCA space, Pattern 1 (normal gait) was distributed near the center, while Pattern 2 was localized on one side of PC1, indicating a different movement tendency from Pattern 1. Patterns 3 to 5 were spread along PC1 and PC2, showing broader variation. These results indicate that PCA effectively extracted structural differences between gait patterns.

4.1.2 Clustering

K-means clustering (K = 5) was applied to the principal component scores obtained from PCA to classify segments based on waveform similarity. This method aimed to extract common and different waveform features,

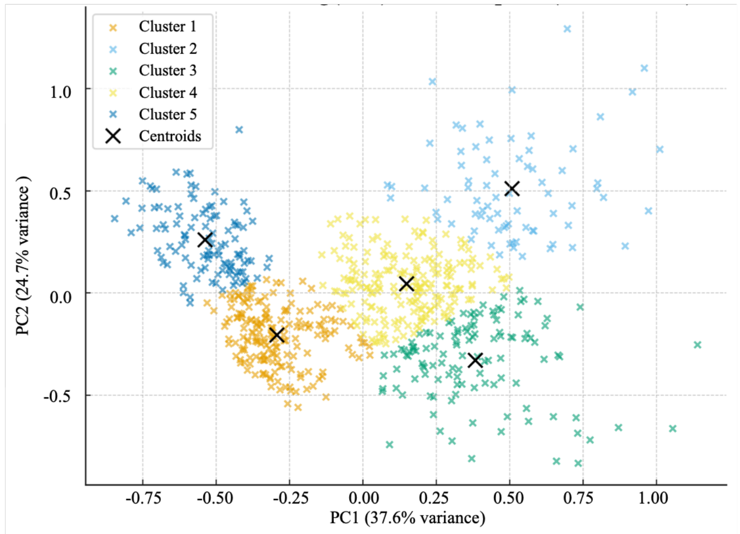

Figure 4: K-means Clustering (k=5) on PCA space (PC1 vs. PC2)

independent of gait pattern type. The clustering results in PCA space showed clear separation of clusters along the principal component axes (Figure 4). Clusters 1 and 5 were located close together, forming distinct local areas separate from other clusters. Clusters 2 to 4 were more dispersed from the negative side of PC1 toward the center, indicating that multiple abnormal gait patterns coexisted in these clusters.

Figure 5 shows the Z-score waveforms for each cluster. Z-scores were calculated with Pattern 1 (normal gait) as the reference. Intervals exceeding ± 2 were treated as regions with pronounced waveform characteristics. On the X-axis (rotation), clear waveform differences appeared between clusters. Cluster 5 showed small amplitude and flattened waveforms with slower rhythm. Cluster 1 showed clear periodicity and a symmetrical shape. On the Y-axis (anterior–posterior tilt), all clusters showed periodic structure, indicating consistent movement. Cluster 1 had larger amplitude and wider anteroposterior motion, while other clusters showed smaller amplitude but maintained periodicity. On the Z-axis (lateral tilt), waveform differences between clusters were small, showing stable periodic rhythm.

On the W-axis (postural stability), differences appeared in smoothness and amplitude. Cluster 5 showed flattened waveforms with minimal variation, while Clusters 1 and 3 had clear amplitude cycles and stable rhythm.

The cluster composition ratios are summarized in Table1 1. In Pattern 1 (normal gait), Cluster 1 accounted for about 98%, representing the baseline waveform structure. In Pattern 2 (Trendelenburg gait), Cluster 5 occupied about 75% of the total. In Patterns 3 to 5, Clusters 3 and 4 increased in proportion, showing a mixture of waveform structures.

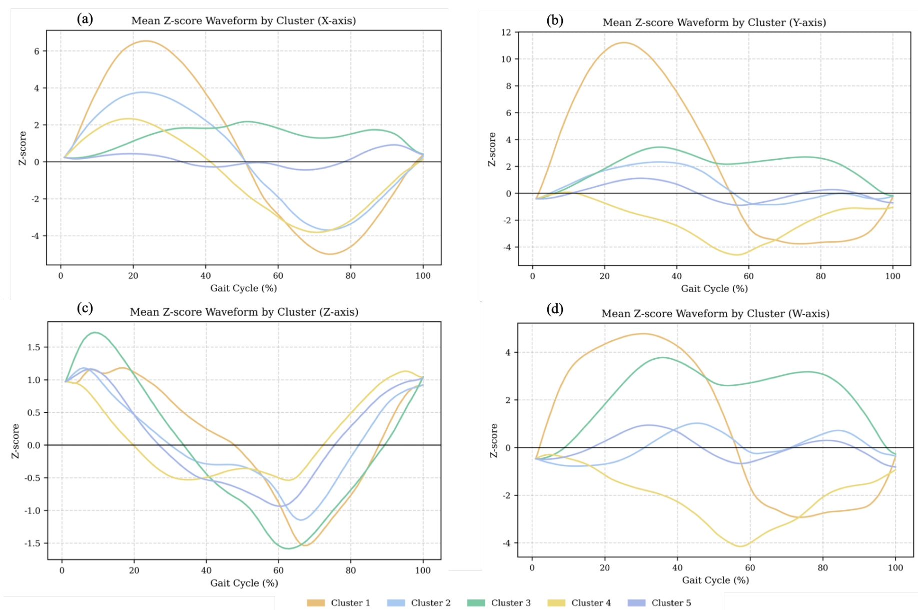

Figure 5: Mean Z-score waveforms by cluster.
(a) X-axis, (b) Y-axis, (c) Z-axis, (d) W-axis.

This trend in cluster composition matched the separation structure seen in PCA space, reflecting differences in waveform shape related to movement characteristics.

These results indicate that the X and W axes mainly contributed to cluster differentiation, while the Y and Z axes maintained periodic and stable structures. This finding shows that quaternion-based gait waveforms can be structurally classified according to waveform shape characteristics.

4.1.3 Classification Model Construction

A support vector machine (SVM) with a radial basis function (RBF) kernel was used for classification. The interpolated and offset-corrected quaternion waveform (400-dimensional vector) was used as the input feature.

The results of 5-fold cross-validation (CV) showed an average accuracy of 0.83 (95% CI: 0.81–0.84) and a Macro-F1 score of 0.84 (95% CI: 0.82–0.85). Repeated 5×10 CV also produced similar results (Acc = 0.83 ± 0.03, F1 = 0.84 ± 0.03), confirming the model's reproducibility. In Leave-One-Subject-Out (LOSO) cross-validation, the accuracy decreased to 0.74 (95% CI: 0.69–0.78) and the Macro-F1 score to 0.71 (95% CI: 0.67–0.76), indicating the influence of inter-subject variability (Table 2).

Table 3 shows the Precision, Recall, and Macro-F1 scores for each gait pattern in 5-fold CV. Patterns 1 and 2 achieved high discrimination accuracy, while Patterns 3 to 5 showed lower accuracy. The LOSO results

Table 1: Cluster composition ratio across gait patterns

Pattern	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
1	98.13	0.00	0.00	0.00	1.87
2	24.65	0.00	0.00	0.00	75.35
3	19.12	6.62	25.74	48.53	0.00
4	3.47	24.31	22.92	49.31	0.00
5	7.10	20.00	32.90	39.35	0.65

Values are expressed as percentages (%).

Table 2: Classification performance under different validation schemes

Method	**Accuracy**	**Macro-F1**
5-fold CV	0.83 (0.81–0.84)	0.84 (0.82–0.85)
Repeated 5×10 CV	0.83 ± 0.03	0.84 ± 0.03
LOSO	0.74 (0.69–0.78)	0.71 (0.67–0.76)

Values are expressed as percentages (%).

(Table 4) showed that Patterns 1 and 2 maintained high accuracy (F1 = 0.95), but Patterns 3 to 5 ranged from 0.59 to 0.67, showing stronger participant dependency.

The confusion matrix (Figure 4) revealed frequent misclassifications between Patterns 3 and 4, and between Patterns 4 and 5, indicating similarities in waveform shape among these patterns.

4.2 Discussion of Results

This study extracted structural features of gait patterns using quaternion waveforms and quantitatively evaluated differences between patterns. Principal component analysis (PCA) visualized the overall structure of waveform variation, and clustering identified latent groups based on waveform similarity. The obtained quaternion waveforms were also used as input features for support vector machine (SVM) classification, and recognition performance was evaluated using multiple validation methods. Based on these findings, the relationship between waveform structure and classification performance is discussed below.

4.2.1 Interpretation of Waveform Structure

Visualization of the principal component (PC) space using PCA showed that each gait pattern was distributed nonlinearly, with major variation along the PC1 axis (Figure 3). PC1 and PC2 mainly reflected the X- and Y-axis components, indicating that pelvic rotation and tilt were the primary sources of variation. Pattern 1 (normal gait) was concentrated near the center, showing high density and consistent waveform reproducibility. Pattern 2 was localized on one side of PC1, forming a distinct region

Table 3: Performance metrics (5-fold CV)

Pattern	**Precision**	**Recall**	**F1**
1	1.00	0.99	0.995
2	0.99	1.00	0.993
3	0.83	0.76	0.79
4	0.64	0.75	0.69
5	0.75	0.68	0.71

Table 4: Performance metrics (LOSO CV)

Pattern	**Precision**	**Recall**	**F1**
1	0.94	0.96	0.95
2	0.96	0.94	0.95
3	0.67	0.66	0.67
4	0.60	0.63	0.61
5	0.60	0.58	0.59

from Pattern 1. Patterns 3–5 showed broader spread along PC1 and PC2, suggesting overlapping structures. These distributions indicate that the balance of pelvic motion differs by gait pattern and that PCA effectively extracted structural differences related to movement characteristics.

K-means clustering (K = 5) produced localized distributions in PCA space, with each cluster showing characteristic waveform structures defined by amplitude, symmetry, and periodic modulation. In composition ratios, about 98% of Pattern 1 belonged to Cluster 1, representing stable periodic waveforms. Cluster 5 accounted for about 75% of Pattern 2, showing reduced amplitude and flattened periodicity. Patterns 3–5 contained multiple clusters, indicating greater heterogeneity in waveform structure. This suggests that abnormal gait characteristics arise not from a single factor but from the combined influence of multiple motion elements such as rotation, tilt, and lateral displacement. The spread in PCA space thus reflects the diversity of complex motion components inherent in the waveform structure.

Comparison of average Z-score waveforms across clusters showed that periodic variation in the X and W axes was the main discriminating factor. Cluster 1 exhibited strong periodicity and consistent phase shifts, indicating stable self-similar waveform shapes. Cluster 5 showed small amplitude fluctuations and reduced periodic changes, resulting in lower signal complexity. These results suggest that waveform stability and nonlinear amplitude modulation serve as key information for cluster separation. Therefore, differences in Z-score waveforms reflect temporal stability and reproducibility within the waveform itself, rather than simple amplitude differences.

In summary, quaternion waveforms represent diverse walking structures through a combination of periodic and nonlinear variations across

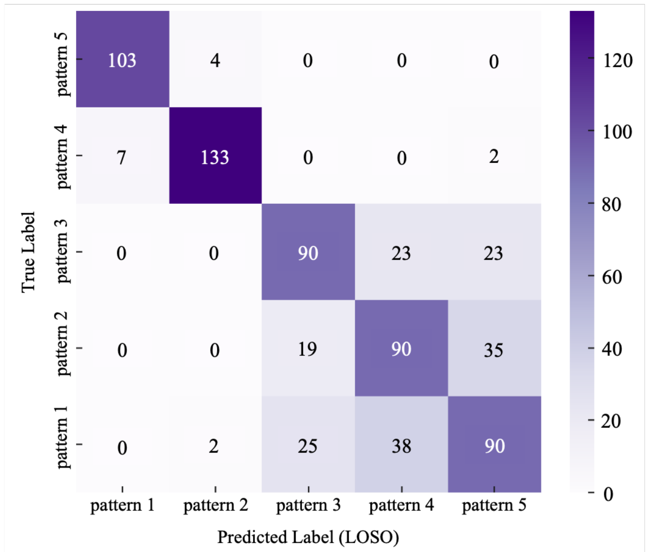

Figure 6: Confusion matrix of SVM Classification (LOSO CV)

multiple axes. The structural differences extracted by clustering reflect rhythm stability and waveform reproducibility inherent in the data. These waveform features form the fundamental information that contributes to classification model construction.

4.2.2 Validation of Classification Performance Using SVM

Classification using the SVM achieved similar results in both 5-fold and repeated cross-validation, with an average accuracy of 0.83 and a Macro-F1 score of 0.84. These results indicate high classification accuracy and confirm that quaternion waveforms function as stable features. The consistency across repeated cross-validation suggests that the model was less affected by data partitioning and could reliably learn waveform structures. However, performance decreased in Leave-One-Subject-Out (LOSO) cross-validation, with an accuracy of 0.74 and a Macro-F1 score of 0.71. LOSO cross-validation evaluates the model on participants not included in training, making inter-subject variability more directly reflected in the classification results. Therefore, participant-specific motion variations are considered to be one of the factors influencing classification performance. The decline in accuracy during LOSO corresponds to the clustering results. Patterns 1 and 2 formed clear clusters with strong periodicity and high waveform similarity, which enabled stable recognition. In contrast, Patterns 3–5 were distributed across multiple clusters and showed variations in amplitude and phase, making class boundaries less distinct and reducing accuracy. The confusion matrix also showed frequent misclassifications between Patterns 3 and 4, which were located close together in the clustering space. This indicates that heterogeneity in waveform structure among participants was a main factor that reduced classification performance. Although the accuracy decreased in LOSO validation, the model still achieved a certain level of performance, suggesting that quaternion waveforms may capture pattern-specific characteristics beyond individual differences. Overall, the recognition accuracy of the SVM was closely related to internal cluster structure, such as periodic stability and amplitude variation. The structural consistency of quaternion waveforms appears to be a key factor influencing model learning accuracy. Future improvements in feature extraction and regularization that consider cluster structure may enhance recognition performance across participants.

5 Conclusion

This study examined a method to identify five types of abnormal gait patterns using quaternion waveforms obtained from smartphone-mounted inertial measurement units (IMU). Analysis of waveform structures using PCA and clustering showed that structural and periodic differences could be extracted between gait patterns. In addition, SVM classification achieved high recognition accuracy (Acc = 0.83, F1 = 0.84), confirming that quaternion waveforms are effective features for representing gait characteristics. These findings support a quantitative understanding of gait motion based on sensor data and provide a foundation for objective and automated motion assessment in physical therapy.

However, waveform heterogeneity caused by inter-subject differences affected classification performance. Mixed cluster structures were associated with misclassification, indicating that future model design should consider individual variation.

For future work, it is necessary to refine the model for clinical application using the waveform structures obtained from simulated walking as a reference. Because actual patients show greater variability and asymmetry in movement, developing a model that maintains recognition stability under waveform fluctuations and structural diversity will be essential. Furthermore, comparing waveform features between simulated and patient data will help verify model consistency and improve generalization. These steps will contribute to establishing a practical framework for applying sensor-based gait analysis in clinical settings. The abnormal gait patterns analyzed in this study were simulated by healthy participants and do not necessarily represent gait patterns in clinical patients. Therefore, further validation using patient gait data is required.

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