Original Article

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The Advantage of Gait Pattern Assessment in Patients With Osteoarthritis Using Pearson Correlation Coefficient and SMAPE: A Case Series

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Objective: To assess patient gait ability by capturing both trend and scale aspects, this study proposes a method using the Pearson correlation coefficient and symmetric mean absolute percentage error (SMAPE).
Methods: Gait patterns from three patients with hip osteoarthritis (OA) were analyzed using kinematic and kinetic data. In each case, using MAPE or Pearson correlation alone failed to provide a reliable assessment, revealing limitations in capturing the full characteristics of gait patterns.
Results: The combined use of Pearson and SMAPE effectively identified gait abnormalities across all cases. This integrated approach offered a more accurate and comprehensive evaluation than single-metric methods.
Conclusion: The findings highlight the importance of considering both trend and scale in gait analysis. The proposed dual-metric methodology overcomes the limitations of conventional and single-metric approaches, enabling a clearer understanding of gait characteristics in patients with hip OA.

Keywords: Hip osteoarthritis, Gait analysis, Hip joint, Locomotion, Correlation of data

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INTRODUCTION

Patients with hip osteoarthritis (OA) demonstrate abnormal gait patterns [1,2]. Subsequently, artificial hip joint replacement surgery is performed, followed by gait rehabilitation The ultimate goal is to enable patients with hip OA to achieve a normal gait pattern [3-5]. Quantifying gait ability at each stage in this comprehensive process is crucial. This allows for an intuitive assessment of both the surgical and rehabilitative effects [6-8]. There has been significant research conducted on the quantitative assessment of gait ability through gait experiments [9-13].

Gait analysis using motion capture equipment and force plates is being extensively employed to analyze the quantitative characteristics of hip OA patients' gait by comparing various variables with normal gait [14-17]. Such comparisons can be applied even to small datasets and offer quantitative results that are easy to interpret intuitively. They provide a straightforward way to assess gait differences without relying on complex models or large sample sizes. This straightforwardness stems from the fact that the metrics are normalized and bounded, which enables consistent and intuitive interpretation.

The gait data derived from the motion capture sensors such as Vicon and Optitrack is in the form of time-series data. Gait ability can be evaluated based on how similar the patients' gait-time-series data is to the gait-time-series data of the healthy controls [18-20]. The closer a patient's gait is to that of healthy controls' gait data, the more it can be considered as approaching normal gait. Conversely, the more it diverges from healthy controls' gait data, the more it can be regarded as abnormal gait.

The gait data, represented as time-series data, should be analyzed with consideration for both trend and scale similarity [21,22]. A commonly employed approach for assessing the similarity of time-series data is through the use of the Pearson correlation coefficient. Conversely, a variety of metrics have been utilized to assess scale similarity. Nevertheless, each metric is associated with inherent limitations, and recent research has focused on employing the symmetric mean absolute percentage error (SMAPE) metric as a means to mitigate these drawbacks [22-25]. By combining the Pearson coefficient and SMAPE score, this study aims to offer a more comprehensive and clinically meaningful assessment of gait. Furthermore, it presents case-specific examples that reveal the limitations of using either metric alone, thereby contributing a practical perspective for future gait assessment protocols as preliminary study. This study was conducted in the process of identifying indices for gait assessment and classification, as reported in Choi et al. [22].

METHODS

Subject

Three hip OA patients as seen in Table 1 involved in the study were diagnosed with hip OA within the past month. Participants diagnosed with hip OA and included in this study were classified as grade 3 or 4 based on the Kellgren–Lawrence grading system. All selected patients were deemed suitable candidates for total hip arthroplasty, with classification confirmed through clinical evaluation by an orthopedic specialist. Individuals with OA grades 0 to 2 were excluded, as they were not indicated for surgical intervention. Furthermore, participants with any prior musculoskeletal disorders affecting the lower limbs, other than hip OA, were also excluded. All gait assessments were conducted within three months following radiographic diagnosis of hip OA.

A total of 16 healthy subjects (8 female and 8 male; age: 56±9 years; weight: 64±10 kg; height: 163±7 cm) were recruited as the control group. None of the participants had a history of gait-related disorders. The healthy control dataset employed in this study was identical to that reported in our previous publication, without any modification. The dataset was collected independently of the case patient data, ensuring that the selection was blinded to the case results and thus eliminating the risk of post-hoc bias. In addition, all healthy control data had been anonymized in accordance with institutional and regulatory requirements, which permits reuse in subsequent studies.

For the purpose of comparative analysis, the healthy control dataset was derived from a prior publication by the authors, in which similar experimental protocols were employed [22].

Instruments

The experiments were performed with the Vicon camera (33EA) and force plate (2EA, AMTI). The Plug-in Gait lower limb marker set was used, and markers were attached to specific anatomical landmarks to capture lower limb kinematics. Markers were placed on the anterior superior iliac spines, posterior superior iliac spines, the midpoints of the lateral thighs (between the greater trochanter and lateral femoral epicondyles), the midpoints of the lateral shanks (between the lateral femoral epicondyles and lateral malleoli), lateral femoral epicondyles, lateral malleoli, heels, and the second metatarsal heads. All markers were positioned by an experienced examiner following the standard protocol to ensure consistency and accuracy of data collection.

Marker trajectory data were processed in Vicon Nexus software, where the Plug in Gait model was applied to transform three dimensional marker coordinates into segmental kinematics, and joint angles were subsequently computed through

Table 1. Physical information of hip osteoarthritis patients

	Sex	Height (cm)	Weight (kg)	Affected side	Age (yr)	KL grade
Patient 1	Male	176	70	Left	52	3
Patient 2	Female	163	53	Left	71	4
Patient 3	Male	183	64	Right	62	3

This table presents the physical information of the 3 hip osteoarthritis patients who participated in gait experiment of this preliminary study. KL grade refers to the Kellgren–Lawrence (KL) grading system.

inverse kinematics according to the model's standard pipeline.

Experiment protocol

To induce a natural gait, subjects freely walk 6 minutes on floor. After attaching the marker, subjects walk about 2 m above the force-plate. The subject walked 7 times on the force plates hidden in the blanket. Among them, the data was used when the subject stepped on the force-plate exactly when walking.

Ethical approval declarations

Prior to the experiment, all subjects signed consent forms approved by Kyungpook National University Chilgok Hospital Institutional Review Board (IRB No. 2018-05-008). This study followed the policy statement concerning the Declaration of Helsinki.

Data analysis

Data analysis tool

Data analysis was performed using Python (version 3.6.7, 64-bit) and the packages used were NumPy 1.16.3, Matplotlib 3.0.1, and pandas 0.23.4.

Variables for gait assessment

In this study, the variables, assessed using Pearson correlation coefficient and SMAPE score, can be classified into the kinetics and kinematics aspects. In the kinetics aspect, the focus is on the sagittal direction moments of the hip joint, knee joint, and ankle joint on the affected side. In the kinematics aspect, the focus is on the sagittal direction angles of the hip joint, knee joint, and ankle joint on the affected side. These variables are individually compared with the average value of the healthy controls. The entire gait cycle, spanning from the heel strike of the stance phase to the end of the swing phase, is considered as a single gait cycle. Throughout this process, the time duration was divided into 100 equal intervals to synchronize the gait cycles in each trial. The gait cycle was normalized such that heel strike corresponded to 0% and toe-off to 100% [26,27].

Pearson correlation coefficient for gait similarity in view of trend

Pearson correlation coefficient is an index that quantifies the similarity between two time-series data in view of trend. The Pearson correlation coefficient formula is as shown in Eq. (1):

$$R = \frac{\sum_{i=1}^{N}(H_i - H)(P_i - P)}{\sum_{i=1}^{N}(H_i - H)^2 \sum_{i=1}^{N}(P_i - P)^2} \tag{1}$$

where R represents Pearson correlation coefficient and N represents the number of data points. H_i represents the ith value of healthy subjects' gait time series data, and P_i represents the ith value of the patient's gait time series data. H represents the average value of healthy subjects' gait time series data, and P represents the average value of the patient's gait time series data.

SMAPE for gait similarity in view of scale

SMAPE is an index that quantifies the similarity between two time-series data in view of scale. The SMAPE formula is as shown in Eq. (2):

$$SMAPE = \frac{1}{N}\frac{\sum_{i=1}^{N}|H_i - P_i|}{\frac{|H_i|+|P_i|}{2}} \tag{2}$$

where N represents the number of data points. H_i represents the ith value of healthy subjects' gait time series data, and P_i represents the ith value of the patient's gait time series data. $\frac{|H_i|+|P_i|}{2}$ represents the average of the ith values of healthy subjects and patients. By dividing $|H_i - P_i|$ by this value, it helps resolve the scaling disparity issue and prevents potential division by zero problems [28]. On the contrary, the formula commonly used for MAPE in machine learning is as shown in Eq. (3):

$$MAPE = \frac{1}{N}\frac{\sum_{i=1}^{N}|H_i - P_i|}{|H_i|} \tag{3}$$

The primary difference between MAPE and SMAPE lies in the value used for normalization. While MAPE divides by the magnitude of the reference time series data, SMAPE divides by the average magnitude of the two compared time series. This difference can prevent problems associated with calculations becoming unfeasible when the reference data is zero. Furthermore, concerning MAPE, when the data being compared exhibits a significant scale difference from the reference, an issue arises wherein the MAPE value may appear significantly large or small [20]. In conclusion, SMAPE score can effectively capture the similarity between two time-series datasets, even in the presence of a substantial scale difference [22,28,29].

SMAPE score typically yields values between 0 and 1. As the reference value H_i is derived from data obtained from healthy control, a value approaching zero indicates similarity to gait pattern observed in healthy control. To intuitively understand gait ability, an index known as SMAPE score is employed, and SMAPE score formula is as shown in Eq. (4):

$$SMAPE\ score = 1 - SMAPE \tag{4}$$

SMAPE score close to 1 indicates gait ability similar to that of the healthy control, while a score closes to 0 suggests a deviation from the healthy control.

RESULTS

As shown in Table 2, the hip, knee, and ankle joint angles and moments of three patient cases were compared with those of healthy controls, and the results are presented in terms of the Pearson correlation coefficient, MAPE, and SMAPE scores.

Case 1

Fig. 1 represents the SMAPE scores and Pearson correlation coefficients of the first patient and a graph of the hip angle and knee angle in the sagittal direction. For hip angle, the patient's Pearson coefficient for healthy controls is 0.96, MAPE is 12.58, and SMAPE score is 0.74. For knee angle, the patient's Pearson coefficient for healthy controls is 0.74, MAPE is 2.59, and SMAPE score is 0.67.

Case 2

Fig. 2 represents the SMAPE score and Pearson correlation coefficients of the second patient and a graph of the hip moment and knee moment in the sagittal direction. For knee moment, the patient's Pearson coefficient for healthy controls is 0.93, MAPE is 2.16, and SMAPE score is 0.73. For ankle moment, the patient's Pearson coefficient for healthy controls is 0.80, MAPE is 12.17, and SMAPE score is 0.55.

Case 3

Fig. 3 represents the SMAPE score and Pearson correlation coefficients of the hip moment and knee angle in the sagittal direction. For hip moment, the patient's Pearson coefficient for healthy controls is 0.40, MAPE is 3.37, and SMAPE score is 0.61. For knee angle, the patient's Pearson coefficient for healthy controls is 0.08, MAPE is 42.51, and SMAPE score is 0.63.

DISCUSSION

In the case of hip angle as seen in Fig. 1, the Pearson coefficient is remarkably high (0.96), primarily due to the similarity in trends, despite the fact that the patient's gait does not exhibit similar scale range of hip angle when compared to the gait of the healthy control. In the case of knee angle, despite the small scale between gait data, distinct trends emerge, leading to a relatively low Pearson correlation coefficient (0.74). This indicates that the Pearson correlation coefficient effectively captures variations in gait patterns. On the other hand, in view of scale, the difference between healthy and patient, in knee angle has decreased. It can be observed that both SMAPE score (hip angle: 0.74, knee angle: 0.67) and MAPE (hip angle: 12.58, knee angle: 2.59) effectively reflect this difference. With MAPE, effective tracking of similarity is observed; however, it is not straightforward to discern whether the MAPE value (from 12.58 to 2.59) aligns with the gait pattern compared to SMAPE score (from

Table 2. Comparison of joint kinematics and kinetics between patients and healthy controls

Case	Index	Hip angle	Knee angle	Ankle angle	Hip moment	Knee moment	Ankle moment
Case 1	Pearson	0.96	0.74	0.58	0.63	0.94	0.75
	MAPE	12.58	2.59	20.10	1.82	3.17	9.74
	SMAPE	0.74	0.67	0.58	0.67	0.74	0.60
Case 2	Pearson	0.93	0.79	0.56	0.72	0.93	0.80
	MAPE	0.70	4.65	16.67	1.33	2.16	12.17
	SMAPE	0.74	0.67	0.54	0.70	0.73	0.55
Case 3	Pearson	-0.87	0.08	-0.24	0.40	-0.74	0.37
	MAPE	12.95	42.51	2.43	3.37	7.25	20.85
	SMAPE	0.51	0.63	0.62	0.61	0.59	0.62

This table compares the hip, knee, and ankle joint angles and moments of three patient cases with those of healthy controls, presenting the values of the Pearson correlation coefficient, MAPE, and SMAPE scores. Pearson refers to the Pearson correlation coefficient, and SMAPE refers to the SMAPE score. MAPE, mean absolute percentage error; SMAPE, symmetric MAPE.

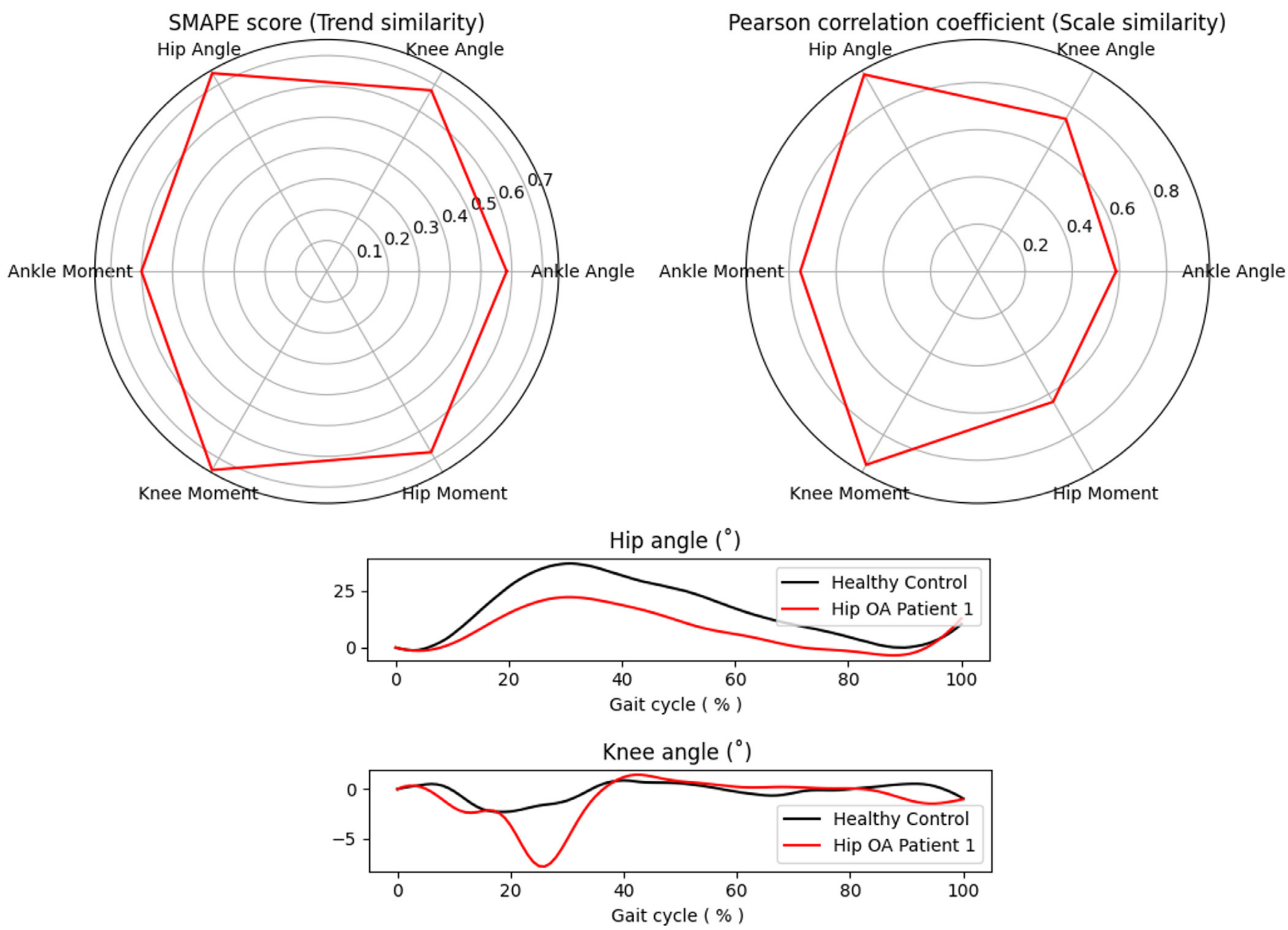

Fig. 1. This figure depicts the results of the second trial of gait experiment for patient 1. The upper graph on left side illustrates SMAPE scores for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of scale similarity. The upper graph on right side illustrates Pearson correlation coefficients for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of trend similarity. The lower graphs illustrate the hip angle and knee angle of affected side in the sagittal direction. The black lines represent the average hip and knee angle for gait of healthy controls, and the red lines represent the hip and knee angle of the hip OA patient, respectively. SMAPE, symmetric mean absolute percentage error; OA, osteoarthritis.

0.74 to 0.67). This is because MAPE normalizes only with respect to the reference data, that is, healthy control data between the two time series data. Therefore, when the scale of the reference data is significantly larger or smaller than the comparison data, the MAPE value can become very small or large, regardless of the similarity in scale.

In the case of knee moment as seen in Fig. 2, the knee moments of healthy controls and patients exhibit similarity in terms of trend and scale. The Pearson coefficient (0.93) and SMAPE score (0.73) represents relatively high values, while MAPE (2.16) represents relatively low values. On the other hand, in the case of ankle moments with low similarity between healthy control and patient, the values of Pearson coefficient (0.80) and SMAPE score (0.55) decreased, and the MAPE (12.17) increased. In other words, it is evident that all three indicators (Pearson coefficient, MAPE, SMAPE score) appropriately demonstrate similarity in normal case.

In the case of knee angle as seen in Fig. 3, the limitation of MAPE is highlighted. In situations where a substantial scale difference exists between healthy control and patient data, the MAPE value (42.51) of hip moment becomes excessively large, making it impossible to intuitively determine gait ability. Conversely, in the case of hip moment, due to the large scale of both two data, although the difference is large, the MAPE value (3.37)

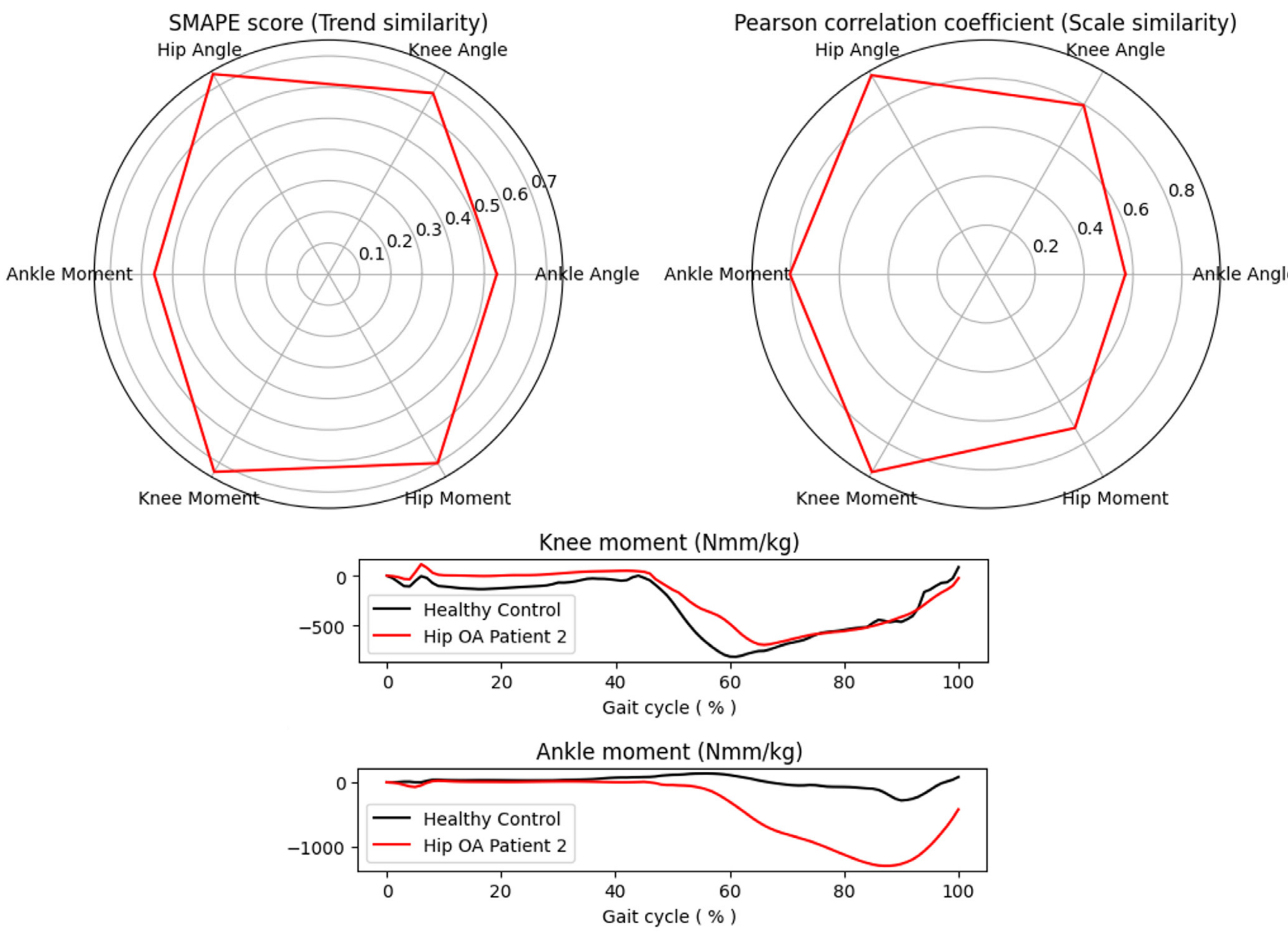

Fig. 2. This figure depicts the results of the second trial of gait experiment for patient 2. The upper graph on left side illustrates SMAPE scores for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of scale similarity. The upper graph on right side illustrates Pearson correlation coefficients for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of trend similarity. The lower graphs illustrate the knee moment and ankle moment of affected side in the sagittal direction. The black lines represent the average knee and ankle moment for gait of healthy control, and the red lines represent the knee and ankle moment of the hip OA patient, respectively. SMAPE, symmetric mean absolute percentage error; OA, osteoarthritis.

is overwhelmingly smaller than the knee angle result. In summary, the Pearson correlation coefficient is sufficient for evaluating the trend aspect of a patient's gait pattern, but it is incomplete as it fails to account for scale-related differences. MAPE is capable of capturing such scale-related aspects. However, when patient gait data include values close to zero, MAPE may produce disproportionately large values regardless of actual similarity. Additionally, when there is a significant scale discrepancy between the healthy control and patient data, MAPE can yield misleadingly large or small values, independent of their scale similarity. The SMAPE score mitigates these limitations. Even when patient gait values are very small or scale differences are large, SMAPE score still provides a stable and interpretable score that better reflects scale similarity.

The Pearson correlation coefficient is widely used and valuable for its ability to intuitively demonstrate the trend similarity between two time series data [30-34]. However, Pearson correlation only captures the similarity in trends between two datasets and does not consider the similarity in the scale aspect of the data [35]. Even if there are significant differences in the magnitude of the forces or moments occurring during gait, the Pearson correlation coefficient will yield a value close to 1 as long as the increasing and decreasing trends are similar. In the case of patients, there is often a significant limitation in gener-

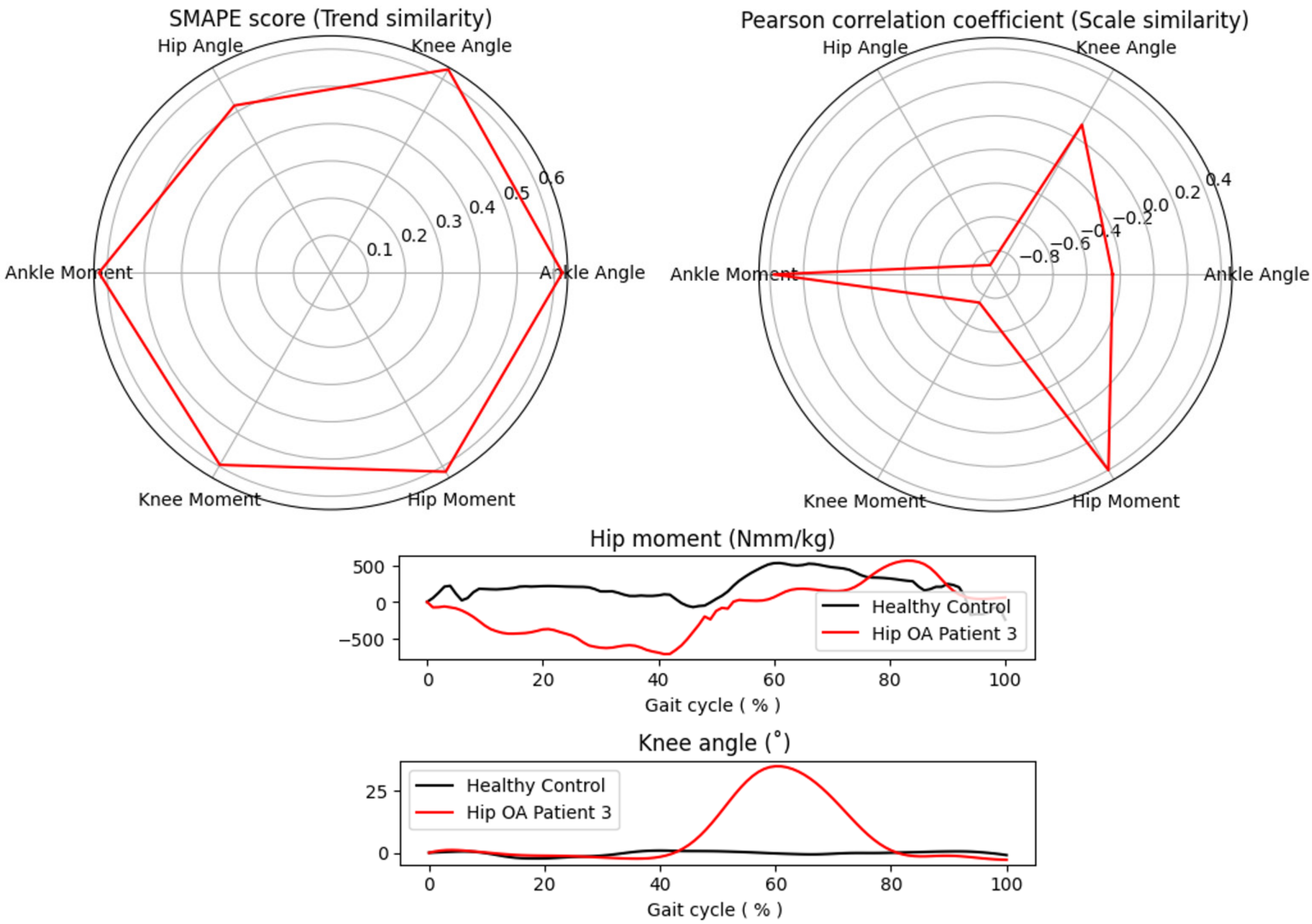

Fig. 3. This figure depicts the results of the third trial of gait experiment for patient 3. The upper graph on left side illustrates SMAPE scores for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of scale similarity. The upper graph on right side illustrates Pearson correlation coefficients for kinetics and kinematics, with red indicating gait scores of hip OA patient in terms of trend similarity. The lower graphs illustrate the hip moment and knee angle of affected side in the sagittal direction. The black lines represent the average hip moment and knee angle for gait of healthy controls, and the red lines represent the hip moment and knee angle of the hip OA patient, respectively. SMAPE, symmetric mean absolute percentage error; OA, osteoarthritis.

ating adequate force or a markedly restricted range of motion during the gait process [36-39]. Considering these characteristics of the patient, the patient's gait data must be evaluated in terms of scale as well as trend when compared to the healthy controls.

In this regard, when analyzing similarity using only Pearson correlation, it may lead to the conclusion that the gait patterns of the healthy controls and patients are similar, as long as the trends align, without accounting for the differences in scale. On the other hands, to compare such scale differences in time-series data, a commonly used technique in machine learning is MAPE [40-42]. While MAPE has traditionally been used to evaluate the similarity between predicted and actual values in regression tasks, it has also been employed to compare the scale-related similarity between two time-series datasets, including applications in gait analysis [42-44]. However, MAPE has limitations when one of the time series data to be compared is significantly larger in scale, the MAPE value is too small or too large regardless of the similarity [20]. Additionally, it cannot handle cases where the denominator is zero. It is also challenging to intuitively understand the error magnitude. This difficulty arises because MAPE produces an absolute value rather than a value within a specific range. In response to these shortcomings, SMAPE is proposed as a supplement [28,29]. Since SMAPE divides the error value by the average of the magnitudes of the two time series data, it can offset the effects of

Table 3. Trend and scale sensitivity characteristics of Pearson correlation coefficient, MAPE, and SMAPE score

Index	Trend sensitivity	Scale sensitivity	Characteristics
Pearson correlation coefficient	High	Not related	Captures similarity in overall pattern (trend), regardless of magnitude differences
MAPE	Not related	High	Reflects magnitude differences only, independent of trend similarity
SMAPE score	Moderate (partially related)	Moderate	Balances both trend and scale by using a symmetric normalization, offering a proportional evaluation

MAPE, mean absolute percentage error; SMAPE, symmetric MAPE.

significant scale differences between them. Additionally, dividing by the average ensures that the calculation is not impeded even if one of the time series values is zero. Lastly, the resulting value ranges between 0 and 1, making it easier to intuitively understand the difference [28,29,45,46].

Certainly, relying solely on SMAPE is not advisable. In gait analysis, the trend similarity, which indicates appropriate movements at appropriate times, is also crucial. Similarity in scale alone does not ensure natural gait [26,27,47,48].

This approach enables a numerical, model-free interpretation of gait dynamics that can support or even replace traditional expert assessments [49,50]. It is particularly useful in clinical settings with small sample sizes, as it allows for intuitive and scalable evaluations of gait patterns without relying on complex machine learning models. Furthermore, our method aligns with prior studies that have adopted dynamic and quantitative metrics for gait assessment.

Table 3 provides a summary of the trend and scale sensitivity characteristics of the three metrics. Although SMAPE does not directly measure trend similarity in the same manner as the Pearson correlation coefficient, its symmetric normalization allows the error to be partially influenced by the relative variation between actual and predicted values. As a result, SMAPE reflects not only magnitude differences but also captures, to a moderate extent, the consistency of trend, thereby providing a more balanced evaluation across cases.

Limitation and future work

This study proposes that Pearson correlation and SMAPE score can serve complementary roles in evaluating gait characteristics. However, this interpretation is based on a limited number of cases, and further validation using a larger and more diverse dataset is required to confirm its generalizability. Although SMAPE score offers advantages over MAPE, particularly in handling near-zero values, it still shows limitations when faced with large scale discrepancies. Due to its normalization, SMAPE score may show limited variability even when the underlying time-series differ significantly in both trend and scale. To address this, future research will explore modified versions of SMAPE score, such as incorporating weights or applying correction coefficients, to enhance its responsiveness to clinically meaningful differences. Finally, while the reference data used in this study was cross-validated with known normative gait patterns during the stance phase, potential variability among reference datasets remains a consideration. Expanding the dataset and applying the proposed approach under various reference conditions will be important directions for future work.

Conclusion

This case study highlights the limitations of using MAPE or Pearson correlation alone in gait analysis. By applying SMAPE score alongside Pearson, we offer a more balanced and interpretable framework that captures both trend and scale differences. While limited in scope, this case-based approach demonstrates the potential of metric-driven gait evaluation. We hope this framework contributes to more transparent and replicable assessments in clinical and research contexts.

CONFLICTS OF INTEREST

No potential conflict of interest relevant to this article was reported.

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AUTHOR CONTRIBUTION

Conceptualization: Choi W. Methodology: Choi W. Formal analysis: Jang J. Funding acquisition: Jung TD. Project administration: Oh S. Visualization: Jung TD. Writing – original draft: Choi W. Writing – review and editing: Jung TD. Approval of final manuscript: all authors.

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