

Optimal Sensor Placement and Minimal Sensor Combination for Step Width Estimation Using Inertial Measurement Unit-based Gait Data

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Step width is an important indicator of gait stability and fall risk, and continuous assessment in daily life is required. Although step width can be estimated from gait data collected using inertial measurement units (IMUs), the minimal IMU placement suitable for continuous use in daily life has not been clarified. In this study, we evaluated the step width estimation accuracy across different sensor configurations using gait data collected from IMUs attached to the waist and shank, and, for the first time, an IMU embedded in the insole. Gait data from 24 healthy males were used, and step width was estimated using a deep learning model to evaluate the performance of each sensor configuration. Overall, the combination of insole and waist IMUs showed the highest accuracy, achieving a mean absolute error (*MAE*) of 39.95 ± 13.39 mm, and among single sensor configurations, the insole IMU achieved the best performance with an *MAE* of 45.41 ± 14.87 mm. Considering ease of attachment and practical use in daily life, the insole IMU may be a promising sensor configuration that enables high accuracy step width estimation with minimal burden.

1. Introduction

Step width is defined as the lateral distance between the heels at initial contact^(1,2) and is widely used as a gait parameter. It plays an important role in evaluating gait stability, assessing fall risk, and informing clinical interventions.^(1,3–8) For example, older adults with a history of falls have been reported to exhibit greater variability in step width, suggesting that step width variability may serve as an indicator of fall risk.^(1,4,7,8) In particular, step width variability has been reported to increase markedly under faster walking speed conditions,⁽⁸⁾ and may provide more sensitive information for fall risk assessment than anterior–posterior gait parameters such as walking speed and stride length. Therefore, evaluating step width contributes to the

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assessment of gait stability and is important for identifying changes associated with increased fall risk and declines in walking function.

Traditionally, several methods have been used to measure step width, such as marker-based or markerless motion capture systems and force plates. While these methods enable highly accurate measurements, the measurement devices are large and expensive, limiting the environments such as laboratories and hospitals. In addition, measurements conducted in controlled laboratory settings tend to make participants aware that they are being observed, leading them to focus their attention on walking. As a result, such assessments can evaluate the walking capacity that participants are able to maximally demonstrate, but may not necessarily reflect walking performance in real-life situations.⁽⁹⁾ Furthermore, walking in daily life is affected by various factors, including divided attention, fatigue, and environmental conditions, and therefore exhibits natural variability. Therefore, short-term laboratory-based assessments may not be sufficient to capture actual declines in walking function or instability. For this reason, it is important to continuously evaluate gait parameters, including step width, in daily living environments.

To address this issue, in recent studies, the estimation of step width using inertial measurement units (IMUs) has been investigated.^(10–13) For example, Díaz *et al.*⁽¹⁰⁾ estimated step width from IMUs attached to both thighs, both shanks, and the waist in healthy adults, achieving a mean absolute error (*MAE*) of 1.91 cm. Wang *et al.*⁽¹¹⁾ applied deep learning to estimate step width from IMUs placed on both shanks and the waist in healthy individuals and patients with ataxia, reporting *MAEs* of 2.9 and 3.3 cm, respectively. Furthermore, Decker *et al.*⁽¹²⁾ demonstrated that step width can be estimated with an error of 1.6 cm in terms of root-mean-square error (*RMSE*) using deep learning with a single IMU worn on the ear of healthy adults. These studies indicate that differences in IMU placement and estimation methods affect the accuracy of step width estimation. Therefore, comparing various sensor configurations under identical conditions is essential for identifying the optimal sensor placement for step width estimation.

Considering continuous use in daily life, it is important to identify the minimal sensor configuration that enables the high-accuracy estimation of step width with minimal burden on the wearer. Even if a sensor can estimate step width with high accuracy, its practicality may be compromised if multiple sensors must be worn daily, as this increases the burden and decreases usability. However, none of the previous studies were on the evaluation of the estimation accuracy using the same dataset, making direct comparison of results difficult. Therefore, the optimal sensor configuration that balances estimation accuracy and wearability has not yet been clarified.

To address this gap, in this study, we aim to compare the accuracy of step width estimation across different sensor numbers and placements using a single, consistent dataset. Building on previous studies,^(10,11,13) we examine three sensor locations, namely, the waist, the shanks, and the foot using an insole sensor, which is newly explored in this study. Step width estimation using insole-based sensors has not been sufficiently investigated so far. By evaluating these configurations under identical conditions, we seek to identify the minimally burdensome sensor setup suitable for continuous step width monitoring in daily life. To our knowledge, this work is

the first on examining optimal sensor configurations while jointly considering estimation accuracy and the practical burden of daily sensor wear.

2. Data, Materials, and Methods

2.1 Participants

A total of 24 healthy students (age range: 20–24 years; height: 1.71 ± 0.05 m; body mass: 63.8 ± 14.0 kg) participated in the study. Prior to the experiment, each participant self-reported their height, weight, presence of fatigue, and any lower-limb injuries. Only individuals who reported no fatigue or lower-limb injuries and who were able to walk without assistive devices were included. This study was conducted with the approval of the Kanazawa Institute of Technology Ethics Committee (Approval number: 2502011). All participants were provided with both oral and written explanations of the study procedures and gave written informed consent before participating in the experiment.

2.2 Measurement of gait data

We collected gait data using IMUs, insole-type sensors, and a markerless motion capture system to estimate step width. Figure 1 shows the sensor placement. On the basis of previous studies,⁽¹¹⁾ the sensors were attached to the waist and shanks, and in this study, we additionally placed insole-type sensors inside the shoes to measure foot data. Participants wore IMUs (Movella DOT, Movella Inc., United States; sampling rate: 120 Hz) at the back of the waist and the shanks and shoes with insole-type sensors (OpenGo Sensor Insoles, Moticon ReGo AG,

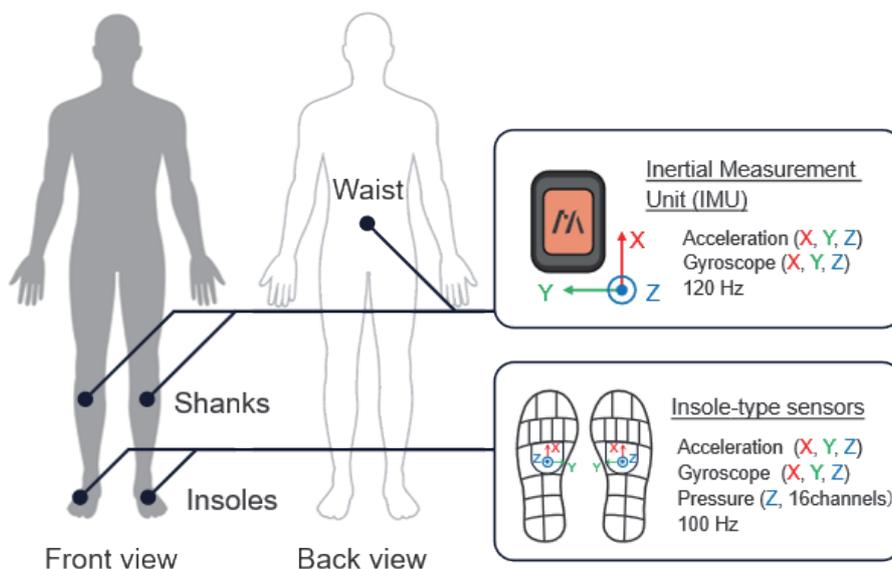


Fig. 1. (Color online) Sensor placement.

Germany; sampling rate: 100 Hz). The IMUs recorded three-dimensional acceleration and gyro data. The insole-type sensors contained both IMUs and pressure sensors, providing three-dimensional acceleration and gyro data from the IMUs and 16-channel pressure data from the pressure sensors. It is important to note that the estimation was based exclusively on IMU data. Conversely, the pressure data was utilized solely for the purpose of identifying the gait cycle. A markerless motion capture system (Miquis Video Plus, Qualisys AB, Sweden, sampling rate: 100 Hz; Theia3D, v2023.1.0, Theia Markerless Inc., Canada) was used to obtain three-dimensional joint coordinates, which were used to calculate step width. The insole-type sensors and the motion capture system were synchronized using a Sync Box (Moticon ReGo AG, Germany).

The experiment was conducted in a laboratory with a straight walkway of 5.5 m. Participants walked under six sets of conditions, combining three gait speeds (normal, slow, and fast) with two step width conditions (normal and wide). The instructions for each gait speed were as follows: “Walk at your normal speed”, “Walk slower than usual”, and “Walk faster than usual”. Each condition lasted three minutes.

Before the measurements, the insole-type sensors (pressure sensors) were calibrated, and participants practiced walking to familiarize themselves with the procedure. The experiment was conducted following the protocol shown in Fig. 2. Participants first performed walking trials at normal speed with the normal and wide step width conditions in that order. After completing the normal-speed trials, the slow- and fast-speed trials were conducted in a randomized order for each participant. At the start of each measurement, participants performed a single vertical jump following a verbal cue from the experimenter to synchronize all sensors, and then began walking after a second cue. They walked back and forth along the straight walkway until the measurement was completed.

Step width was calculated using the heel coordinates (L_HEEL and R_HEEL) obtained from the markerless motion capture system. Figure 3 shows the definition of step width. Following previous studies,^(1,2) step width was defined as the mediolateral distance between the heels at the initial contact of each foot.

2.3 Data preprocessing

In this study, the collected gait data were preprocessed as follows. First, a fourth-order Butterworth low-pass filter with a cutoff frequency of 10 Hz was applied to remove noise. Next,

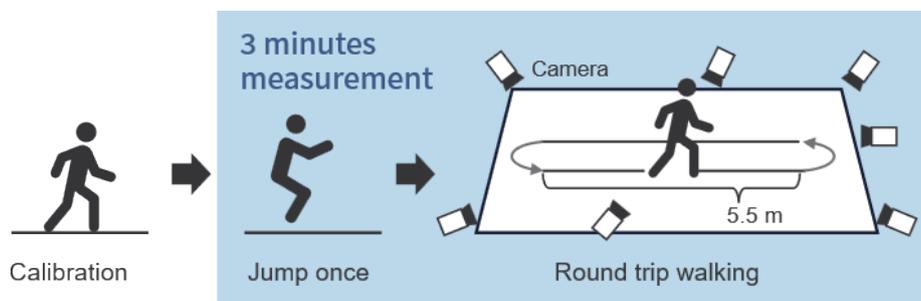


Fig. 2. (Color online) Procedure for measuring step width and gait data.

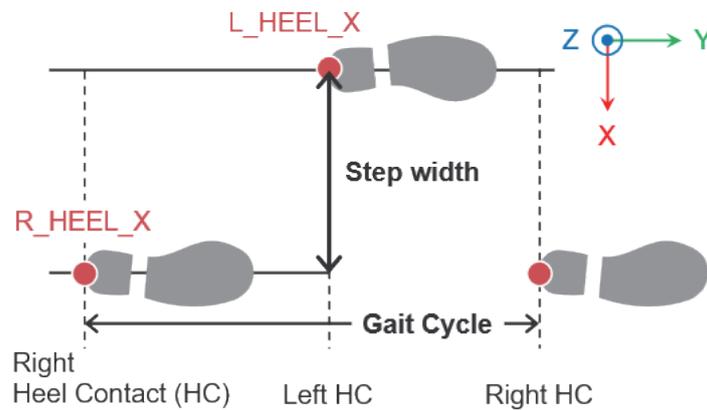


Fig. 3. (Color online) Definition of step width.

the IMUs and insole-type sensors were time-synchronized using acceleration waveforms obtained during the jump. The joint coordinate data were aligned at the same starting point as the insole-type sensor data. Initial contact was then detected from the pressure data of the insole-type sensors, and the data were segmented into individual gait cycles. Finally, each gait cycle was resampled to 101 points.

2.4 Step width estimation

To estimate step width, a deep-learning-based estimation method, bidirectional long short-term memory (BiLSTM), proposed in a previous study,⁽¹¹⁾ was employed. Figure 4 shows an overview of the model. To compare the estimation accuracy of step width among different sensor configurations, multiple combinations of sensor inputs were prepared. The model inputs consisted of IMU data from the waist, shank, and insole corresponding to one gait cycle. The output was the step width corresponding to the same gait cycle. The input data was then normalized to a range of -1 to 1 , employing the minimum and maximum values for each sensor.

For model training, the *MAE* (L1 loss) was used as the loss function, and the Adam optimizer was adopted. The learning rate was set to 1×10^{-3} , the batch size to 256, and the number of epochs to 80. The model was implemented using Python 3.11 and PyTorch 2.4.0.

2.5 Evaluation of estimation accuracy

To evaluate the accuracy of step width estimation, leave-one-subject-out cross-validation (LOSO-CV) was performed. Among the data collected from 24 participants, the data of one participant were used as the test set, while data of the remaining 23 participants were split into 18 participants for training and 5 participants for validation. This process was repeated for all participants so that estimation results were obtained for each individual.

To compare the estimation accuracy across different sensor configurations and attachment sites, five evaluation metrics were calculated: *MAE*, *RMSE*, Pearson's correlation coefficient (PCC), Spearman's rank correlation coefficient (SCC), and the intraclass correlation coefficient

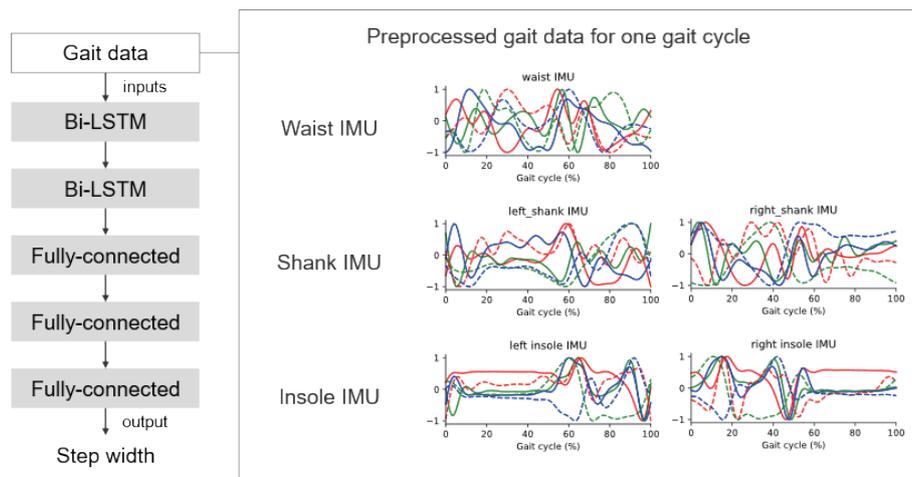


Fig. 4. (Color online) Overall model architecture.

for absolute agreement [ICC(2,1)]. *MAE* and *RMSE* were used to evaluate the magnitude of the estimation error, whereas *PCC* and *SCC* assessed linear and rank correlations, respectively. According to the result of a previous study,⁽¹⁴⁾ the degree of agreement based on ICC was interpreted as follows: poor (<0.5), moderate (0.5–0.75), good (0.75–0.9), and excellent (>0.9). All evaluation metrics were calculated on the basis of the reference step width values obtained from the motion-capture system and the corresponding estimates derived from IMU data, and were computed using Python 3.11.

3. Results

3.1 Dataset

The dataset used in this study consisted of synchronized IMU data and motion capture measurements collected from 24 participants under six walking conditions. Table 1 summarizes the dataset used in this study. Regardless of the step width condition, the gait speed increased in the order of slow, normal, and fast. The step width was larger under the wide condition than under the normal condition. The number of gait cycles, which was used as the input unit for the model, was approximately balanced across all conditions.

3.2 Step width estimation

Table 2 and Fig. 5 show the results of step width estimation. Among the individual sensors, the insole-type sensor achieved the highest accuracy, with an *MAE* of 45.41 mm. It also exhibited few outliers. In contrast, the IMU attached to the shank showed the largest estimation error and tended to have large intersubject variability. When multiple IMUs were combined, the combination of the waist and insole sensors achieved the highest accuracy, with an *MAE* of 39.95 mm. Regardless of the number of sensors used, ICC values ranged from 0.75 to 0.90. However,

Table 1

Summary of the dataset collected in this study, showing gait speed, step width (mean \pm SD), and the number of gait cycles across walking conditions.

| Walking condition | | Gait speed (m/s) | Step width (mm) | Number of gait cycles |
|-------------------|------------|------------------|--------------------|-----------------------|
| Gait speed | Step width | | | |
| Slow | Normal | 0.64 ± 0.15 | 152.60 ± 52.16 | 2305 |
| | Wide | 0.58 ± 0.14 | 333.94 ± 75.03 | 2299 |
| Normal | Normal | 0.93 ± 0.16 | 115.62 ± 37.08 | 2610 |
| | Wide | 0.86 ± 0.12 | 300.61 ± 79.77 | 2667 |
| Fast | Normal | 1.19 ± 0.22 | 145.78 ± 36.86 | 2506 |
| | Wide | 1.13 ± 0.21 | 326.40 ± 64.53 | 2721 |

Table 2

Step width estimation accuracy across IMU placements.

| Placements | MAE (mm) | RMSE (mm) | PCC | SCC | ICC |
|----------------------|-------------------------------------|-------------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| Insole | 45.41 ± 14.87 | 57.18 ± 18.53 | 0.88 ± 0.07 | 0.86 ± 0.07 | 0.81 ± 0.13 |
| Waist | 49.72 ± 14.09 | 60.79 ± 16.96 | 0.87 ± 0.09 | 0.85 ± 0.09 | 0.78 ± 0.12 |
| Shank | 59.06 ± 39.78 | 69.28 ± 40.35 | 0.87 ± 0.11 | 0.86 ± 0.10 | 0.75 ± 0.22 |
| Insole, Waist | 39.95 ± 13.39 | 49.88 ± 19.27 | 0.90 ± 0.10 | 0.88 ± 0.08 | 0.84 ± 0.14 |
| Insole, Shank | 49.48 ± 31.50 | 59.08 ± 31.90 | 0.90 ± 0.09 | 0.88 ± 0.08 | 0.80 ± 0.19 |
| Waist, Shank | 48.91 ± 28.46 | 58.01 ± 29.38 | 0.89 ± 0.12 | 0.87 ± 0.12 | 0.80 ± 0.20 |
| Insole, Waist, Shank | 44.45 ± 25.39 | 53.19 ± 26.41 | 0.92 ± 0.08 | 0.89 ± 0.08 | 0.82 ± 0.17 |

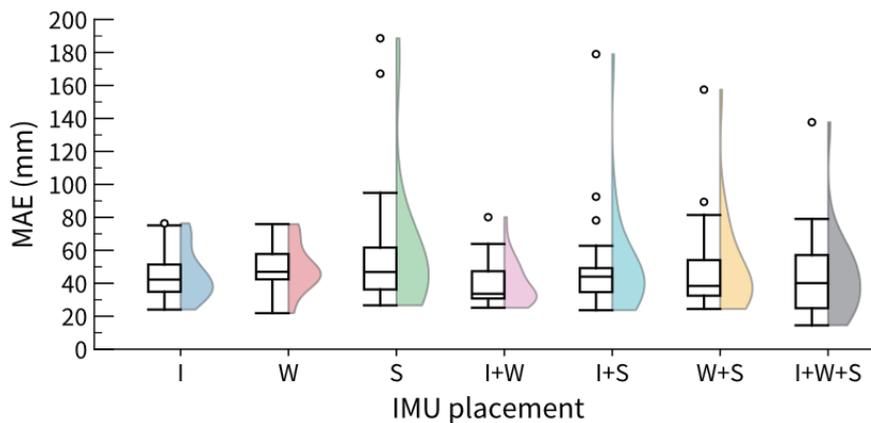


Fig. 5. (Color online) Violin boxplot of MAE for step width estimation across different sensor configurations. I: Insole, W: Waist, S: Shank.

configurations including the shank showed more outliers. No clear bimodal MAE distributions were observed in any IMU configuration, suggesting the absence of distinct error subgroups.

4. Discussion

The purpose of this study was to evaluate the accuracy of step width estimated from gait data considering daily-life applications and to identify the minimal sensor configuration that enables high-accuracy estimation. As a result, among individual sensors, the insole-mounted IMU

achieved the highest accuracy. When multiple sensors were combined, the combination of the insole sensor and the waist-mounted IMU showed further improvement in estimation accuracy.

4.1 Dataset

The results presented in Table 1 demonstrate that the subjects adhered to the stipulated walking conditions as instructed. Specifically, walking speed increased in the order of slow, normal, and fast, regardless of the walking condition. Furthermore, the step width was wider under the wide condition than under the normal condition. These findings indicate that the dataset adequately represents variations in gait speed and step width, making it suitable for evaluating sensor configurations under different walking conditions.

4.2 Effects of placement and number of IMUs on estimation accuracy

The position and number of sensors are key factors affecting the accuracy of step width estimation. When using a single sensor, differences in estimation accuracy were observed depending on the sensor placement, as shown in Table 2 and Fig. 5. These differences are likely attributable to the distinct characteristics of the data obtained from each location. The highest accuracy was achieved with the IMU embedded in the insole. The foot contains much information related to gait dynamics, such as heel strike and toe-off events. Consequently, foot-mounted IMUs have been applied to gait parameter estimation⁽¹⁵⁾ and the classification of gait under fatigue conditions.⁽¹⁶⁾ In addition, since the sensor is fixed inside the shoe, its placement remains stable, reducing motion artifacts and contributing to the high estimation accuracy. Conversely, the lowest accuracy was observed with the IMU attached to the shank. This is likely due to variations in sensor placement and orientation during walking, which caused instability in the acquired data. Previous studies have revealed that deviations in the IMU mounting position or angle can significantly decrease the estimation accuracy of kinematic and kinetic data.^(17,18) Collectively, these results indicate that the foot is the most appropriate site for sensor attachment in step width estimation.

When multiple IMU sensors were combined, estimation accuracy improved compared with the use of a single sensor, as shown in Table 2 and Fig. 5. In particular, the combination of an insole IMU and a waist IMU showed improvements across all evaluation metrics. Moreover, adding a shank IMU further enhanced the estimation accuracy, especially in terms of PCC and SCC. These improvements are likely due to the complementary information obtained from multiple body segments, which helped to compensate for gait characteristics that could not be fully captured by a single sensor. Taken together, these results are consistent with those of previous studies^(10–12) and suggest that the use of multiple IMUs is effective for improving step width estimation accuracy.

The usefulness of the estimated step width can be evaluated on the basis of whether the estimation error falls within a range that can detect clinically meaningful changes. It has been previously reported that the minimum clinically important difference (MCID) in step width between healthy individuals and patients with ataxia is 60 mm.^(11,19) This indicates that the step

width of patients with ataxia is approximately 60 mm wider than that of healthy individuals. Therefore, if the estimation error is less than 60 mm, it may be possible to detect widening trends in step width on the order of the reported MCID, which is a characteristic of ataxia. In this study, the *MAE* met this criterion for all sensor combinations except in the case of the shank-only configuration.

Overall, the achieved estimation accuracy is sufficient to detect increases and decreases in step width for longitudinal monitoring. While this level of accuracy is not appropriate for definitive clinical diagnosis from a single measurement, it may support daily-life applications by enabling the early identification of changes in step width and potentially helping to prevent declines in walking stability through continuous monitoring. Moreover, this accuracy level is particularly relevant when step width is assessed repeatedly in the same individual, where within-subject trends and sustained deviations are more informative than a single absolute estimate.

4.3 Wearability and practicality

When applying step width estimation in daily life, it is important to consider the trade-off between estimation accuracy and practicality. While the use of multiple IMUs improved estimation accuracy, attaching sensors to multiple body segments such as the waist and shank increases user burden and raises concerns about practicality in daily environments. The insole-type IMU achieved relatively high accuracy even when used alone, suggesting that it is a suitable option for daily monitoring. Because the insole sensor is fixed inside the shoe, its position is stable and less affected by intersubject variability in sensor placement compared with waist- or shank-mounted IMUs. Moreover, once attached to the shoe, it can be used continuously with minimal effort, which enhances its usability. Therefore, although the use of multiple sensors is effective in research or clinical environments where high accuracy is required, an insole-only configuration may provide clinically and practically acceptable accuracy for daily-life step width estimation.

4.4 Limitations and future works

This study has several limitations, and further research is required to improve the generalizability and estimation accuracy. First, the participants were limited to young healthy males, which may restrict the generalizability of the findings. To verify this, future studies should include participants across a wider age range and with diverse physical characteristics. Nevertheless, in this study, we employed LOSO-CV to evaluate the generalization performance for each subject, confirming a certain level of intersubject generalizability.

Second, in this study, we used relatively expensive insole-type sensors equipped with pressure sensors. Although the pressure data were used to detect gait cycles with high precision, they were not incorporated into the estimation model. Meanwhile, methods for detecting gait cycles solely from IMU signals have been proposed,⁽²⁰⁾ indicating that pressure sensors are not strictly necessary. Therefore, in future work, this framework could be implemented in a more

cost-effective and practical manner by replacing the sensors with inexpensive IMUs mounted inside shoes and estimating gait cycles from IMU data.

Third, the estimation model used in this study was based on a configuration similar to that in a previous study⁽¹¹⁾ employing IMUs on the waist and shank. Since the optimal estimation method may vary depending on sensor placement, the most suitable estimation approach for step width estimation using insole-type sensors should be investigated in future research.

5. Conclusions

In this study, step width was estimated using IMU sensors attached to different body segments and an insole-type sensor, and the estimation accuracy was compared across sensor configurations. The main findings are summarized as follows.

- The estimation accuracy varied depending on the sensor attachment site, with the insole-type IMU achieving the highest accuracy. This is likely due to its stable attachment and the plethora of gait information obtained from the foot.
- Combining multiple sensors improved estimation accuracy, and the combination of the insole and waist IMUs was particularly effective.
- For all configurations except the shank-only setup, the *MAE* satisfied the MCID (60 mm), indicating clinically useful accuracy.
- While using multiple sensors is effective for improving accuracy, the insole-only configuration demonstrated a good balance between accuracy and practicality for daily use.

These results suggest that step width estimation using an insole-type sensor is promising even in daily life environments. Future work will be focused on expanding the participant population and developing estimation models optimized for insole-based sensing.

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