Segmented Gait Analysis Using Pressure-Sensing Insoles in a Hemiparetic Patient: A Case Study

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***Abstract*—Recent technological advancements in wearable devices equipped with a wide range of sensors have enabled the collection of detailed biomechanical data, offering new possibilities for assessing and supporting rehabilitation in both clinical and everyday settings. However, individuals with unstable health conditions or limited physical activity may find it difficult to directly apply analytical methods developed for healthy individuals. This study investigated gait analysis using smart insoles embedded with pressure sensors in four regions of each sole, totaling eight regions, in an individual undergoing rehabilitation for post-stroke hemiparesis. The patient's gait exhibited distinct characteristics compared to that of healthy individuals. Notable features included fluctuating and inconsistent peak and trough values, irregular peak shapes, variable stride times, marked left–right asymmetry, and the absence of distinct peaks during presumed turning phases. Given these differences, conventional analytical methods were not directly applicable; thus, a new analytical approach was developed. Due to the wide variability in peak amplitudes, applying a uniform threshold for peak detection across the entire dataset was not feasible. Additionally, gait involves steady straight walking and variable-speed phases, such as turning, stepping over obstacles, stopping, and swaying—phases that are particularly challenging for individuals with gait impairments. Analyzing the entire walking period under uniform conditions may obscure important gait characteristics. Based on 1.1 times the mode of the stride time, smart insole data were segmented to distinguish between straight and irregular walking phases, followed by the calculation of mean, peak, and post-peak decline values. This approach enabled an objective evaluation of the effectiveness of a gait-assist robot used in rehabilitation, highlighting the clinical potential of smart insole–based gait analysis.**

Keywords- smart insole; rehabilitation; hemiparesis; gait analysis.

I. INTRODUCTION

Basic movements—such as walking and transitioning between positions, including standing up and sitting down—are essential components of the Activities of Daily Living (ADL). The soles of the feet, being the only body parts in contact with the ground while standing, play a critical role in maintaining posture and balance. Furthermore, owing to their distance from the heart, the feet are prone to poor blood circulation during prolonged periods of sitting or standing. Walking is considered fundamental to health that it is sometimes referred to as the “sixth vital sign” [1]. Therefore, evaluating plantar conditions and mobility is significant both from a functional mobility standpoint and a health monitoring perspective. Gait assessments have been conducted across diverse populations, including older adults [2]–[4]; individuals with central nervous system disorders such as stroke, Parkinson’s disease, and multiple sclerosis [5]–[9]; those with cardiovascular or respiratory diseases [10][11]; those with musculoskeletal conditions such as low back pain [12]; and individuals with cognitive impairments [13]. In recent years, advances in digital technologies have enabled gait assessment using wearable devices [14]–[16], including the development of smart insoles designed to evaluate age- and disease-related changes and support fall prevention [17]–[20]. As insoles are integrated with footwear, smart insoles embedded with pressure sensors allow continuous gait monitoring over time. If wearable devices such as smart insoles become widely available for evaluating ADL such as walking, objective assessments could be conducted in clinical settings during therapist-led rehabilitation as well as in home environments. However, when gait disturbances are severe, applying gait analysis methods developed for healthy individuals may be inappropriate. In this study, we propose a novel gait analysis approach using pressure sensor-embedded smart insoles in a single patient undergoing inpatient rehabilitation following stroke. This case study aimed to demonstrate the feasibility and utility of this approach in a clinical setting.

This study was approved by the Ethics Committee on Research with Humans as Subjects of the Teikyo University of Science. The participant was an individual receiving medical rehabilitation services and was fully informed of the potential benefits and risks of participating in the study. Written informed consent was obtained by occupational therapists from patients undergoing rehabilitation who participated in the study. Section II describes the experimental method, Section III presents the results, Section IV provides a discussion, and Section V concludes the study and outlines future work.

II. EXPERIMENTAL METHOD

A single participant undergoing gait rehabilitation was assessed under three conditions: before, during, and after the use of a gait-assistive robot. The resulting data were analyzed to establish a gait evaluation framework.

A. Devices and Software

A wireless pressure-sensing smart insole, FEELSOLE® (Toyoda Gosei Co., Ltd.), was used in this study. The device was equipped with four pressure sensors positioned at the toe, heel, inside, and outside, enabling measurements at a total of eight points across both feet. Calibration was performed prior to use and consisted of four steps: (1) no pressure applied without inserting the foot into the shoe, (2) standing with both feet, (3) standing on the left foot only, and (4) standing on the right foot only. The insole sampling frequency was 50 Hz. The insole was connected via Bluetooth to an iOS application, ORPHE TRACK® (ORPHE Inc.), which automatically uploaded the data to the cloud. The recorded data were subsequently downloaded in CSV format using the ORPHE ANALYTICS system for further analysis.

Figure 1. Appearance of smart insoles.

For gait rehabilitation, the Orthobot® (FINGGAL LINK Inc.) was used. This device is attached to a Knee–Ankle–Foot Orthosis (KAFO) and helps guide the lower limb toward a desirable movement pattern during walking.

B. Participant and Measurement Method

Gait measurements were conducted on a single male participant in his 70s who was hospitalized and undergoing rehabilitation following a stroke. With the cooperation of the hospital's physical and occupational therapists, gait was assessed under three conditions: before using the gait-assistive robot, during its use, and after its removal. The participant had left hemiparesis and higher brain dysfunction due to a stroke, along with a medical history of traumatic brain injury and left femoral neck fracture. Motor impairments resulting from prior traumatic brain injury were suspected to affect not only the left upper and lower limbs but also the right limbs.

Rehabilitation, including physical, occupational, and speech-language therapies, began the day after stroke onset. Each therapy was provided five times per week, with each session lasting 40 min. Physical therapy included gait training. On day 16 after stroke onset, gait assessment was conducted using a smart insole and gait-assisted robot. Since the participant was unable to walk independently, a physical therapist provided support from behind during the measurement. The gait-assisted robot was attached to the participant's left lower limb. The gait task included straight walking and a U-turn.

C. Gait Characteristics and Analysis Method

For analysis, we excluded the first and last 100 data points recorded at the beginning and end of the measurement period. The raw heel data are shown as the blue line in Figure 2. Our previous study on healthy adults investigated a method for gait assessment using pressure sensor-equipped insoles, and suggested the utility of both peak values and post-peak decline rates at the four insole regions during each step [21]. In the present investigation, the participant's gait was compared with that of healthy controls, and the following distinguishing features were observed: (i) peak and trough values fluctuated and lacked consistency; (ii) peak shapes were irregular, occasionally presenting two successive peaks that produced an "M-shaped" waveform; (iii) the interval between successive heel peaks—that is, the stride time—was inconsistent; (iv) inside and outside pressures on the right foot were reduced; (v) pronounced left–right asymmetry was evident; and (vi) no distinct peaks appeared during periods presumed to correspond to irregular gait while turning.

Due to the wide variation in peak amplitudes, establishing a single threshold for peak detection throughout the entire recording was impractical. Accordingly, the dataset was segmented to exclude intervals with prolonged stride durations, which were assumed to reflect irregular gait. Analysis was focused on periods assumed to represent straight walking. The methods used for data segmentation, peak extraction, and calculation of the post-peak decay rate are described in Section 2) below.

1) Calculation of Stride Time: Since peak values occasionally appeared in rapid succession and irregular forms, a moving average was applied to smooth the data and calculate stride times. The signal was smoothed using a moving average with a window size of 11. Stride time was defined as the interval between two successive heel peaks on the same side (either left or right).

2) Method for Segmenting Insole Data: The mode of stride times was determined based on the values calculated from the smoothed data. Periods with stride times exceeding 1.1 times the modal duration were considered to involve irregular gait events, such as turning or interruptions, and were excluded from the analysis as nonstraight walking. The segmentation procedure involved the following steps:

- Calculation of Modal Stride Time.
  Stride duration was calculated from the smoothed data obtained using a moving average with a window size of 11. Stride duration was defined as the interval between a peak value x and the subsequent peak x+1. Peak values were defined as time points corresponding to the maximum force recorded by the insole sensor at each instance of foot-ground contact. Peaks were detected using the find_peaks function in the SciPy Python Library. Equation (1) defines the threshold used to detect peaks in the smoothed data.

$$thresh\_peak = Min + (Max - Min) \times 0.25 \quad (1)$$

  Subsequently, time bins were created in 0.2-second increments up to the maximum stride duration. Among these bins, the one containing the highest number of stride durations for the right heel—assumed to represent the better-functioning side—was identified, and its upper limit was defined as the modal stride time.
- Exclusion of irregular gait periods.
  Time intervals exceeding 1.1 times the modal stride duration were regarded as irregular gait, such as during turning or interruptions, and were excluded from the analysis to isolate segments representing straight walking. To ensure that the start and end times of the straight walking segments did not overlap with any peak values, a buffer equal to one-fourth of the median stride time of the right heel (calculated after smoothing) was added to both ends of each segment. For analysis, the longest of the identified straight walking segments was used for further examination.

3) Calculation of Mean Values: The mean values for each insole region were calculated using both nonsegmented and segmented raw data.

4) Mean of Peak Values: For nonsegmented and segmented data, the peak values were defined as the maximum force detected at the heel, toe, inside, and outside regions of the insole during each instance of foot-ground contact.

5) Calculation of Decline Rate: The decline rate reflects the decrease in pressure values following each peak. In this study, it was calculated by measuring the difference in weighted averages between adjacent data points. Specifically, the decline rate was defined as the difference between the weighted averages at point x and point x+1. The weighted average was calculated using five consecutive data points: the target point, two preceding points, and two succeeding points. To emphasize the influence of the central value, weights were assigned as follows: 40% to the target point, 20% to the points immediately before and after, and 10% to the secondary points before and after. Among the calculated decline rates, the largest value within each foot-ground contact was defined as the maximum decline rate. These maximum values were extracted for each instance, and their mean was then computed.

III. RESULTS

In this section, the results of the analysis of gait characteristics before, during, and after robot-assisted walking are presented. We compare segmented and nonsegmented data to examine changes in stride time, mean and peak insole values, and decline rates.

A. Data Segmentation

Among the walking periods with irregular time segments excluded, the longest and second longest durations were identified. Figure 2 shows the walking data recorded before the robot was worn and after its removal. The green lines indicate the start times of the extracted segments estimated to represent straight walking, and the yellow lines indicate the corresponding end times.

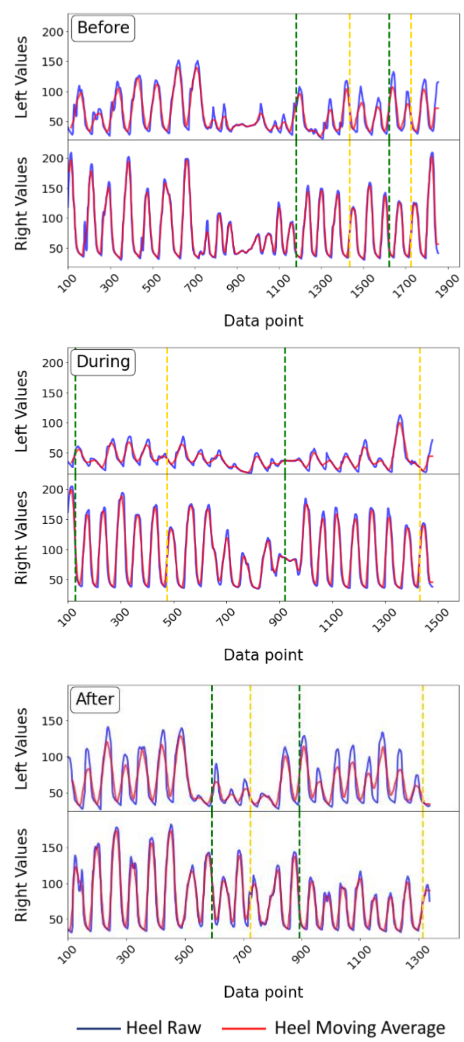

Figure 2. Irregular walking exclusion time.

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Irregular gait periods were excluded from the data recorded before the robot was worn. However, in the data recorded after the robot was removed, some segments presumed to represent an irregular gait were included and misclassified as straight walking. Additionally, in the data recorded while the robot was worn, a small portion of the irregular gait was included among the extracted segments.

B. Stride Time

The average stride times were calculated using the timings of heel peaks on the left and right sides during walking—before wearing the robot, while wearing it, and after its removal. These results, based on both segmented and nonsegmented data (referred to as "split" and "non-split" data), are presented in Figure 3.

Stride time on the left side tended to be longer on the right side, which was considered the better-functioning side. The left stride time was defined as the interval between one left heel contact and the next. After removal of the robot, the overall stride times decreased, and in the split data, the differences in stride times between the left and right sides were reduced. A particularly large difference was observed between the split and non-split data for the left heel.

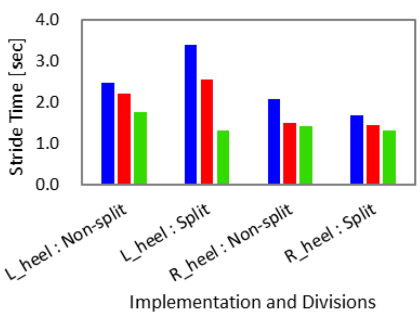

Figure 3. Average stride time from split and non-split data.

Regarding asymmetry, the difference in stride time between the left and right sides was particularly pronounced before robot use, with greater asymmetry observed in the split data compared to the non-split data. As illustrated in the raw data graphs in Figure 2, left–right stride time asymmetry was evident even during walking segments presumed to be straight walking, before and during robot use. This pattern is consistent with the trend shown in Figure 3. However, as shown in Figure 2, the number of foot contacts detected in the split dataset was limited. For instance, prior to robot use, the left stride time could only be calculated over one or two steps. Therefore, although these values indicate a tendency toward left–right differences, they were insufficient to definitively characterize the participant's gait.

C. Mean Values

The mean values of the split and non-split raw data are shown in Figure 4. While the overall trends were similar between the two types, some differences were observed. Specifically, the mean value for the right heel after robot removal was lower in the split data compared to the non-split data, and left–right asymmetry was reduced. Additionally, the mean value of the right toe increased following robot removal. These changes were not apparent in the non-split data; however, the split data revealed that robot use reduced heel asymmetry and increased toe loading.

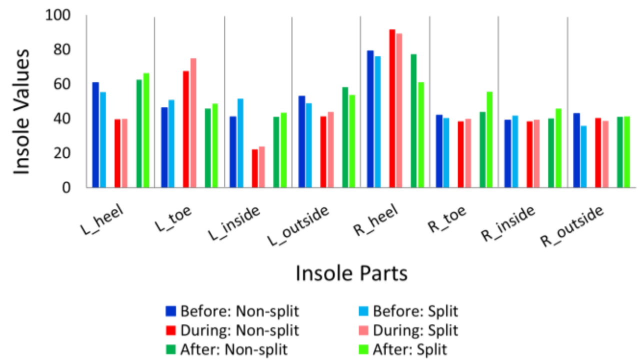

Figure 4. Mean values of insole regions from split and non-split data.

D. Mean Peak Values

The mean peak values for each part of the insole are shown in Figure 5. These results show trends similar to those observed in Figure 4, which displays the mean values for the entire raw dataset. After wearing the robot, the peak values increased at the heel and outside region of the left side—the side on which the robot was worn—compared to before use. On the right side, which was not equipped with the robot, the heel peak values decreased, resulting in a reduced asymmetry between the sides. In addition, the toe peak values on the right side increased.

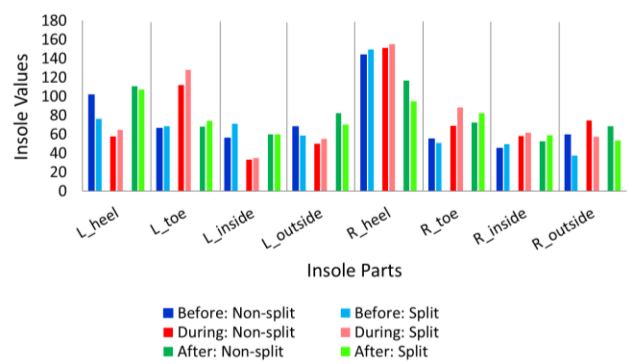

Figure 5. Mean peak values of insole regions in split and non-split data.

E. Decline Rate

The decay rates for each part of the insole are shown in Figure 6. When comparing the average values before and after the removal of the robot, overall decay rates tended to be higher after removal. On the left side, although a slight decrease was observed in the inside region for the split data, increases were observed in the other regions. Notably, a pronounced change in the decay rate was observed at the left heel in the split data. On the right side, a decrease was observed at the heel, whereas other parts showed increased decay rates, with the most prominent increase occurring at the toe. These findings suggest that robot-assisted walking led to a higher rate of change per unit time, particularly on the side where the robot was worn. The differences between the split and non-split data were particularly noticeable at the left heel before robot use and at the right toe during robot use.

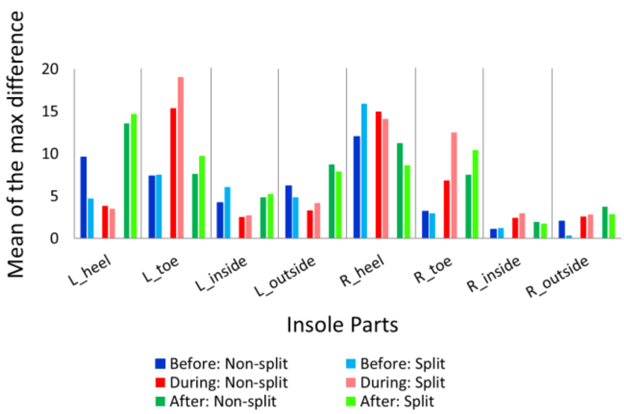

Figure 6. Decrease rates of insole regions in split and non-split data.

IV. DISCUSSION

In participants with gait impairments, the peak and valley values were inconsistent compared with healthy individuals, and M-shaped patterns—characterized by two successive peaks—were observed during periods presumed to correspond to irregular walking, such as U-turns. Therefore, the analysis was conducted using segmented data, excluding these irregular periods. The use of segmented data enables the detection of gait-assisted robot effects. To avoid distortion caused by extremely long or short stride durations, the mode, rather than the mean, was adopted as a representative stride time. Durations exceeding 1.1 times the mode were considered indicative of irregular walking, such as turning or interruptions, and were distinguished from straight walking periods. A lower threshold ensures stricter exclusion of irregular intervals, but risks omitting valid straight walking data. Conversely, a higher threshold allows the inclusion of straighter walking data, but may fail to exclude some irregular periods. These settings should be adjusted by considering the primary focus of the analysis: walking speed and balance ability.

In the segmented dataset, irregular periods were successfully excluded under pre-robot conditions. However, in the post-removal condition, some data from irregular walking phases were not excluded and were instead classified as straight walking. Furthermore, even under robot-wearing conditions, a small amount of irregular data were included. One possible explanation is that the gait-assistive robot improved walking ability, leading to more regular patterns in the better-functioning right limb, even during turning. This trend was also observed in the raw data graph (Figure 2), which showed more consistent insole readings on the right side after robot use. Our previous investigations in healthy adults have also revealed that gait patterns during U-turn phases can resemble those observed during straight walking. This suggests that individuals with a certain level of walking ability may exhibit regular gait patterns, even during turning. Conversely, in the post-removal condition, the right limb (which retained better function) maintained regular patterns even during irregular walking, whereas the left limb (which had worn the robot and had lower functional capacity) exhibited irregular data, highlighting a clear asymmetry in gait regularity. Future studies should consider segmentation based not only on the better-functioning limb, but also on incorporating data from the left and right limbs. The results differed between the segmented and nonsegmented data. However, the number of detected foot contacts in the segmented data was limited. Although these values suggested left–right asymmetry, they were insufficient to clearly characterize the participant's gait. To enhance the reliability of gait characterization, future analyses may need to include the longest segment along with other usable segments to increase the amount of available data.

In the present analysis, the focus was on straight walking, and the longest segment from the divided data was used for evaluation. Irregular walking phases were not analyzed as straight walking. However, Leach et al. demonstrated the importance of assessing fall risk during turning movements [22]. This suggests that future analyses focusing on irregular gait phases could offer valuable insights into mobility assessment. Refining data-segmentation methods and applications remains an important future direction.

Changes were observed in both the peak values and rates of decline in the insole data following robot-assisted walking. Particularly, the segmented data showed a marked increase in the rate of decline of the left heel (on the robot-wearing side) and right toe (on the nonwearing side). These results indicate that robot-assisted walking leads to increased pressure and quicker movement at the left heel and right toe. Additionally, the findings suggest the potential usefulness of segmented data for capturing such changes.

V. CONCLUSIONS AND FUTURE WORK

Walking includes steady-paced straight walking and variable-speed phases, such as turning, stepping over obstacles, stopping, and swaying. Therefore, analyzing the entire walking duration under uniform conditions may obscure critical gait characteristics. This is particularly relevant in individuals with gait impairments, for whom the evaluation of variable-speed phases presents additional challenges. This study focuses on measurements, data analysis, and method development. Notably, using the mode of stride time—rather than the mean—helped minimize the influence of extreme stride time values and enabled effective data segmentation. This approach enabled the evaluation of the gait improvement effects resulting from the use of a gait-assist robot in a rehabilitation setting. Moreover, the practical utility of smart insoles depends on their digital functions and structural design, which play a crucial role in physical comfort and psychological usability, especially in everyday settings outside controlled clinical environments. As this was a single-case study, the generalizability of the results is limited. Future studies should include a larger sample size and further investigate the measurement data, analysis methods, and insole design.

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