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Feature Value Classification Based on the Position Difference of Pressure Sensors Installed in Insoles and Their Outputs

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Abstract: This study focuses on the sensor position in an insole system that aims to detect changes in physical conditions. To reduce the costs, the number of pressure sensors is limited to four. The system evaluates the changes in the load applied to each sensor on the insoles. Commercially available insoles are classified into S, M, and L sizes and cut to fit the shoe size. Consequently, sensors are not always attached at appropriate positions on the insole, and substantial variations are expected to occur because of misalignment. The output characteristics differ significantly depending on the toe sensor position. In particular, the toe length varies considerably among individuals, and the sensor position must be adjusted to suit each individual. The peak value of the sensor output and the steepest slope value at the subsequent decrease are promising feature values. The incorporation of machine learning into the output results, including other sensor positions, is expected to yield more accurate data.

Keywords: Pressure sensors, Insole, Health condition change, Arduino, Bluetooth, Classification, Machine learning.

1. Introduction

Rapid aging is a global problem [1-3] that is expected to become a major societal concern not only in Europe [4] but also in Asia [5]. The number of caregivers for the older adults is expected to increase owing to the declining birth rate, and the number of caregivers for each elderly person is expected to decrease, resulting in the elderly being cared for by the elderly. One primary concern in caring for older adults is that they may become bedridden because of fractures caused by falls.

Several studies have used images and sensors to prevent falls [6-13]. Insole sensors [14, 15], which are commercially available and relatively easy to use, are often used to prevent falls because the gait state is significantly influenced by physical conditions. Whereas these commercial insole sensors were mainly developed for athletes, they have attracted considerable interest because of their relevance to lower limb dynamics that is crucial not only for runners but also for people of all ages. Furthermore, the interest in gait analysis within rehabilitation centers and facilities dedicated to the elderly is increasing.

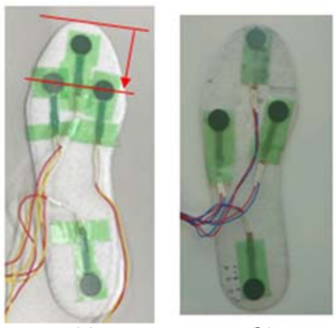
We previously reported a sensor that was used as a reference for determining movement limitation states using data from the insole sensor pressure distribution [16-19]. The e-rubber smart insole, known as FEELSOLE®, was available in three sizes (S, M, and L) with 2 cm increments. In this case, the output of the toes appeared low that raised the question of whether accurately determining the sensor position was important. Because the tip of each toe has a short bone, a slight difference in the sensor ground position may affect the output. For certain diseases and disorders, the information from the toe portion of the insole is important, including hammertoe, a condition in which the toes are bent. The conditions under which the sole of the foot touches the ground and the pressure distribution on the sole at the start of the gait vary depending on the condition of the lower limbs. The heel, in particular, is the most pressured area, and the changes in pressure at the start of the gait are considered parameters that characterize gait and are important in the analysis.

Therefore, we fabricated a device in which a pressure sensor was fixed to the shoe insole using tape to allow the position of the sensor to change arbitrarily. Using this insole, the pressure changes during walking were examined by changing the toe sensor position, and the effects of different sensor positions were investigated.

The research was approved by the Ethics Committee of Teikyo University of Science.

2. Experiment

The pressure distribution screen of a commercially available smart insole shows the pressure applied to the sensor in different colors. In an initial experiment to determine the optimal sensor position, the sensor was placed, as shown in Fig. 1(a), using an Interlink FSR-402 sensor to obtain the foot pressure distribution for comparison with a simplified display. The sensors were affixed to four locations: 15 mm from the toe, 60 mm from the inside and outside of the foot, and 20 mm from the heel. The side with the affixed sensor was positioned downwards. As the experiment progressed, as shown in Fig. 1(b), measurements were obtained by changing the sensor placement position to 80 and 90 mm for the inner and outer sensor positions, respectively. This adjustment aimed to achieve a more accurate distribution of foot pressure. As shown in Fig. 2, the system used an Arduino Nano to convert the analog signals from the sensors into a digital format and sent them to a PC via Bluetooth using a Microchip SBD with PIC24FJ64GB004. The received signals were processed using a program created by processing, and the files were saved. For comparison, smart insole FEELSOLE® was used on top of the fabricated insoles. The output of the homemade insole sensor was approximately 0.5 V lower because of the cushioning effect of the smart insole. A 9 V battery was used for this prototype owing to the unavailability of a polymer battery charger during the prototype phase owing to supply shortage. A self-made insole sensor was attached to the right foot for the measurements. First, sandals were used instead of shoes, this facilitated easy wiring of sensor signals to the Arduino Nano and Microchip SBD BT attached to the top of the footwear. We also performed two types of measurements: one in which the insole sensor was installed inside the sandal, and the other in the shoe.



(a) (b)

Fig. 1. Sensor position.

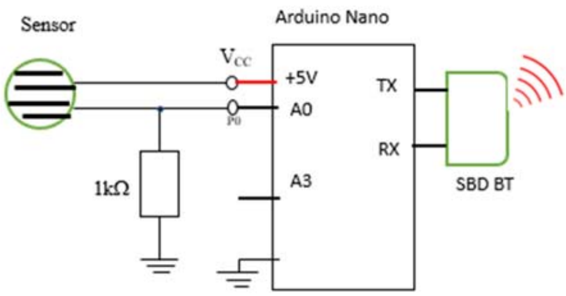


Fig. 2. Measurement system.

During the measurement, the participant walked for approximately 30 or 60 s, with and without motion restriction on the right knee joint, using a supporter, for a distance of approximately 3 m. A video was captured from the front for a separate analysis. When walking, the participant repeatedly performed U-turns and straight turns. The sensor position was varied from the tip of the insole to examine the relationship between the sensor position and the presence or absence of motion restriction in the right knee joint. At 70 mm, the sensor position was lower than that of the inside and outside sensors, as shown in Fig. 1(a).

Furthermore, measurements were taken with the sensor position corresponding to the toe, 50 mm from the tip, that was similar to that of commercially available smart insoles.

Considering that the sensor position in the heel area also significantly affected the measurement results, we conducted measurements at positions 20, 30, and 40 mm away from the heel tip. Furthermore, because sufficient mobility could not be secured depending on the measurement location, measurements were performed by walking in only one direction for up to 3 m without U-turns.

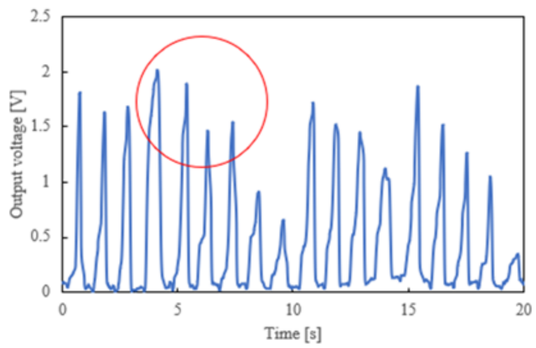
The participant was a male in his 60s. Exercise restriction was simulated using a supporter in the knee area.

3. Results

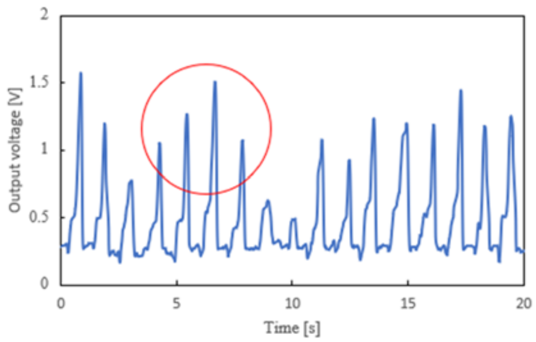
3.1. Output Waveforms from a Self-made Insole Sensor

With the sensor positioned 15 mm from the tip of the insole, the measurement results during walking with and without motion restrictions are shown in Figs. 3(a) and (b), respectively. The position of the peak differed in each cycle, and the output voltage was lower in certain cycles. In the absence of motion restriction, the signal decreased with time.

Assuming that a low-output state below 50 % of the peak value corresponded to the state at the U-turn, we compared the difference between the peak (maximum value) and the minimum values among four consecutive values in the interval up to the low-output value before the first U-turn. In this case, this interval was used as a break. The difference tended to be larger under these limitations. The values of the sensor outputs other than those of the toe sensor were calculated based on the time of the toe sensor output.



(a)



(b)

Fig. 3. Measurement results during walking without (a) and with motion restriction (b).

In measurements that did not involve a U-turn, the measurement distance was short, with a maximum 3 m; therefore, only three sensor peaks were obtained. Therefore, we decided to use the average peak value from these three points and the slope of the point where the rate of decrease was the maximum after the peak.

3.2. Comparison of Average Output Voltages and the Difference Between Maximum and Minimum Output Voltages

The sensor position from the toe was varied from 15 mm to 70 mm. Fig. 4 illustrates two characteristic examples: the average of the four sensor output voltages and the difference between maximum and minimum output voltages. In the figure, Toe represents the case without motion limitation, ToeR represents the case with right knee motion limitation, and the labels marked as dif represent the maximum-minimum voltage differences.

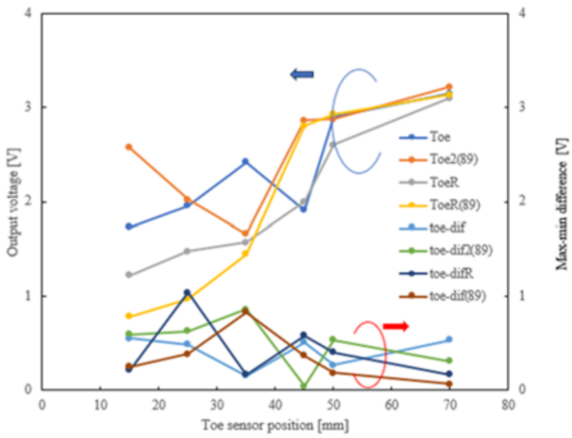


Fig.4. Average of four sensor output voltages and the difference between maximum and minimum voltages.

Different results were obtained when the sensor position of the toe was changed without motion restriction. The output was such that the characteristics shifted to the left, except for the area close to the tip; however, the output voltage at a distance closer to the tip increased. The trend of the difference between the maximum and the minimum values did not change significantly with or without motion limitation, or with different measurements. The data shown as 89 in the figure were measured with the inner and outer sensor positions set at 80 mm and 90 mm from the tip, respectively.

3.3. Change in the Peak Value by the Self-made Device

A decrease in the output voltage was observed with the passage of measurement time when the sensor position on the toe was changed. The variation in the peak value at the sensor position on the toe is shown in Fig. 5. The horizontal axis represents the point number evaluated as the peak, not time. The unit for the number of measuring positions was based on the nature of the evaluation software. The peak points correspond to the measurement times. At 50 mm, the values were almost stable, except at the U-turn point.

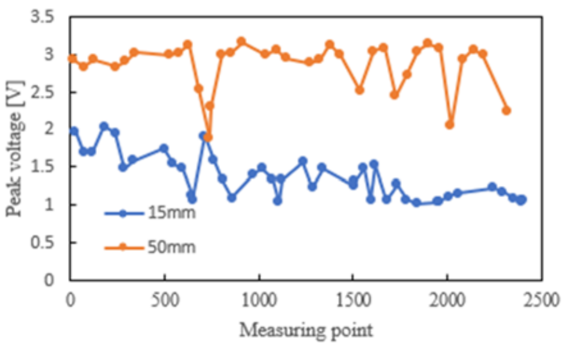


Fig. 5. Change in the peak value with no motion limitation by the self-made device.

Fig. 6 shows an example of the results obtained when the toe sensor position was set at 15 mm and the self-made insole was placed in sandals and shoes. No motion restrictions were applied to the knees during measurement. Compared with the case using sandals, when measurements were taken using shoes, the fluctuation in the width of the peak output was larger, but no decrease in the output signal was observed.

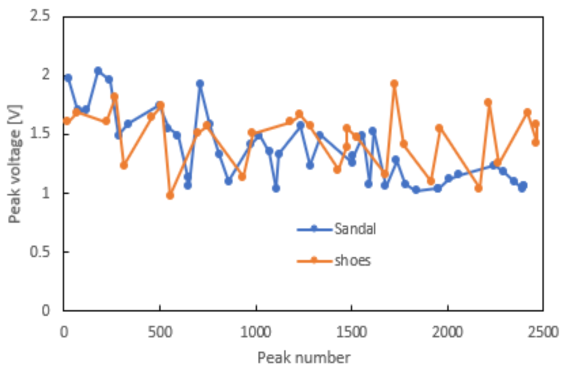


Fig. 6. Comparison of output voltages when a self-made insole was built into a sandal and shoe.

3.4. Output Voltage with Different Heel Positions

Measurements at different heel positions were performed with shoes on. Because the range that could be considered to correspond to the heel was narrow, the sensor positions were only at three points: 20, 30, and 40 mm. The difference between the maximum and the minimum outputs was small, and no influence of the position was observed. When movement was restricted, the closer the sensor was to the end of the calcaneus, the larger was the sensor output; when movement was restricted, the sensor output was smaller. In Fig. 7, N and R represent the presence and absence of movement restrictions, respectively.

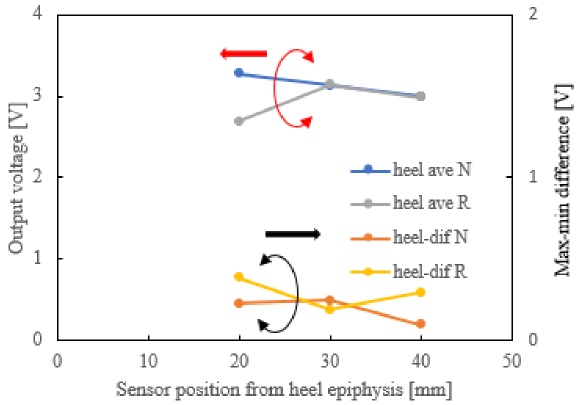


Fig. 7. Output voltage with different heel positions.

3.5. Output from Smart Insole

The output from the smart sensor was obtained for confirmation because the output from the self-made insole sensor decreased with time. The results are shown in Fig. 8. Because the sensor position of the smart insole did not change, slight variations in the amplitude were observed, whereas the period remained relatively constant. This differed from the observed output pattern of the self-made insole sensor.

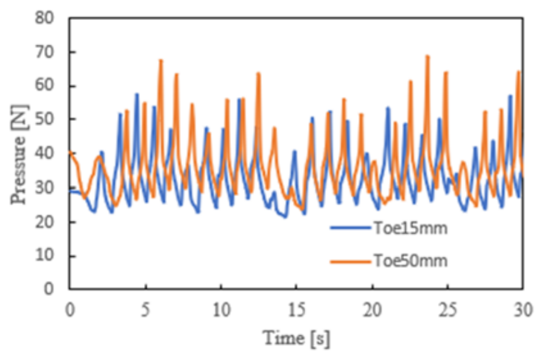


Fig. 8. Output of the smart insole sensor when the position of the self-made sensor was changed.

3.6. Classification

As reported in SEIA' 2022 and our previous paper, the set of peak values and the steepest slope values in the decreasing portion after the peak reflected the participant's characteristics. In the current study, because we did not have sufficient measured data, we did not use machine learning for analysis, but instead investigated the possibility of classifying whether a subject had movement restrictions based on a combination of sensor outputs from four locations and the slope.

Figs. 9 and 10 show the cases where the toe sensor positions were 15 mm and 50 mm, respectively; Support Vector Machine (SVM) was used as the classification method. Figs. 11 and 12 show the cases where a decision tree was used. The data used for this classification were analyzed using the data from shoes. The black circle indicates no movement restriction, and the red circle indicates movement restriction on the right knee. Only the toe sensor position was changed at two points, 15 mm and 50 mm, and the other sensors were set as shown in Fig. 1(b).

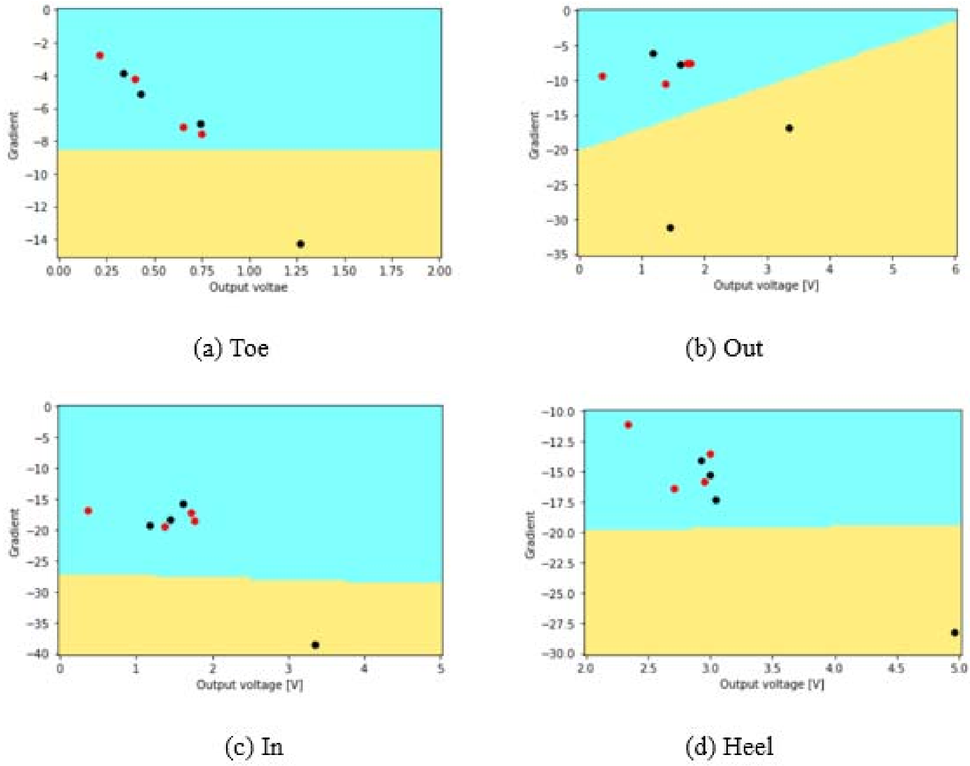


Fig. 9. Classification using the Support Vector Machine method. The toe sensor position was 15 mm.

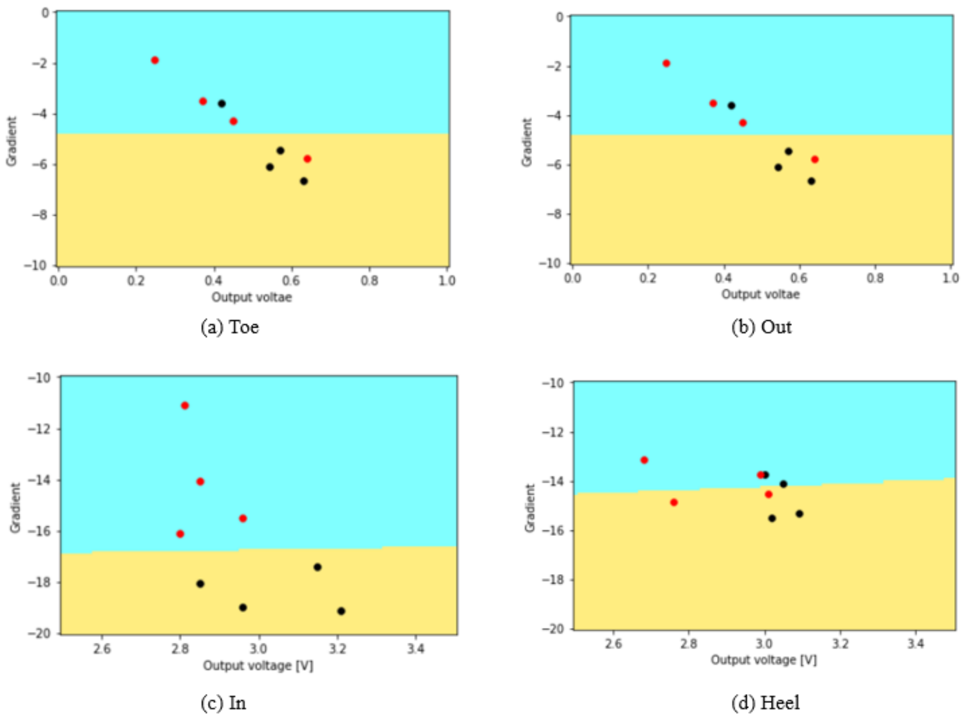


Fig. 10. Classification using the Support Vector Machine method. The toe sensor position was 50 mm.

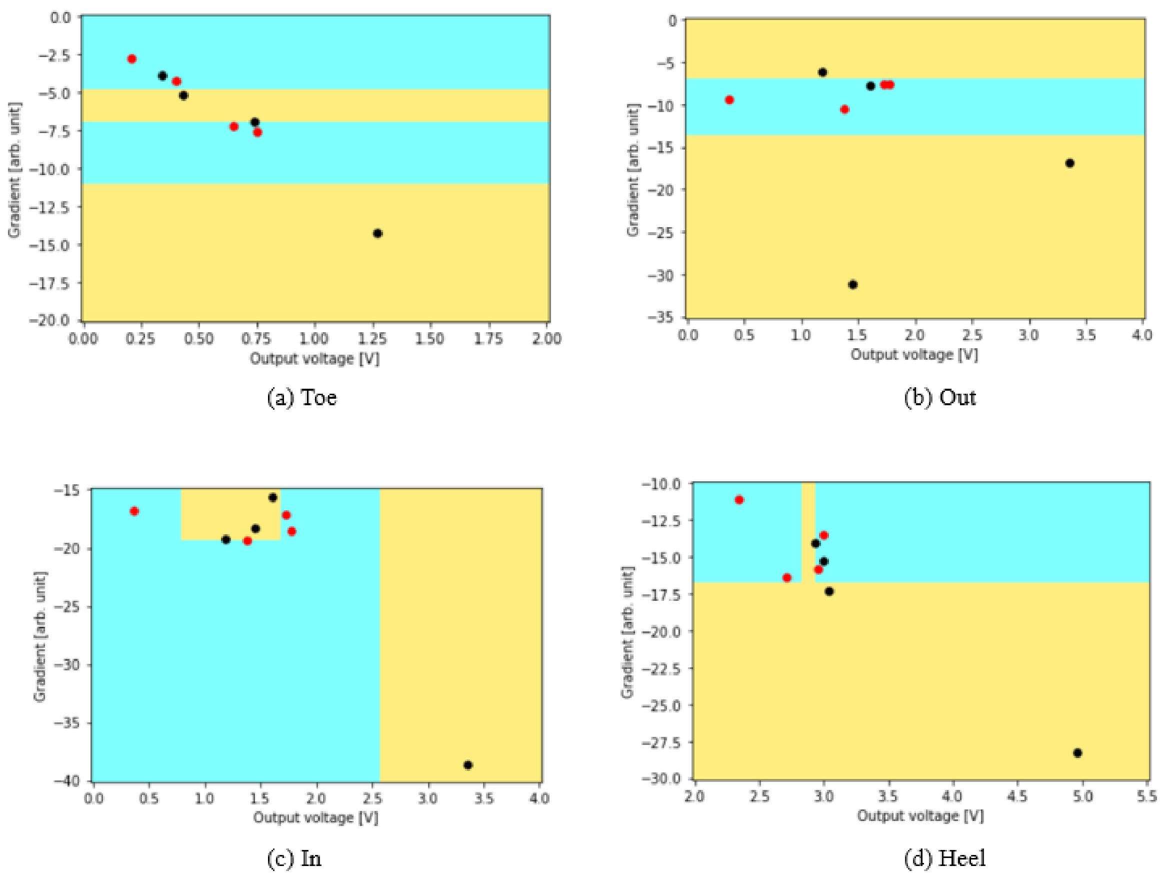


Fig. 11. Classification using the decision tree method. The toe sensor position was 15 mm.

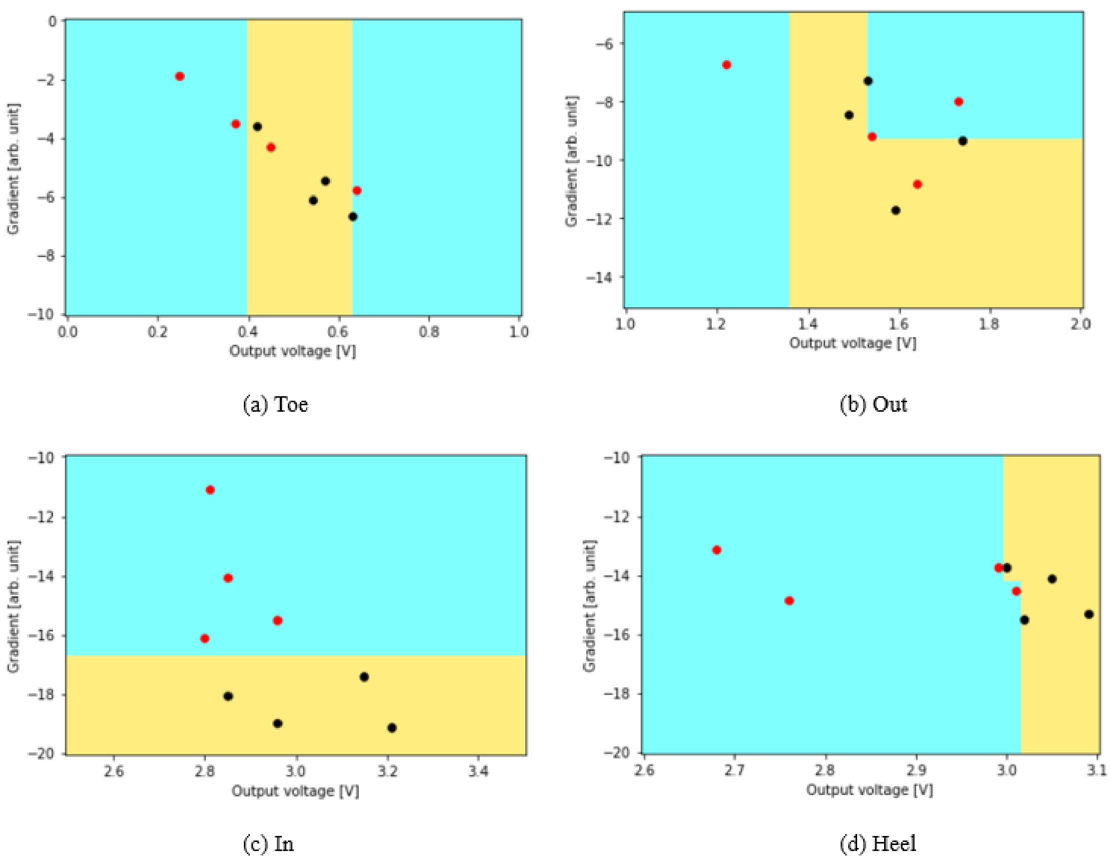


Fig. 12. Classification using the decision tree method. The toe sensor position was 50 mm.

The accuracies of the classification results are presented in Table 1. The accuracy was expressed as a percentage. In this measurement, the accuracy of classification was higher when inner data were used.

Table 1. Difference in accuracy expressed as a percentage depending on the classification method.

	SVM15	SVN50	DT15	DT50
Toe	62.5	75	87.5	87.5
Out	75	50	87.5	87.5
In	62.5	100	100	100
Heel	62.5	50	87.5	100

The classification results were further confirmed using the k-means method, an unsupervised learning method for classification. The triangles in the figure represent the centers of the clusters.

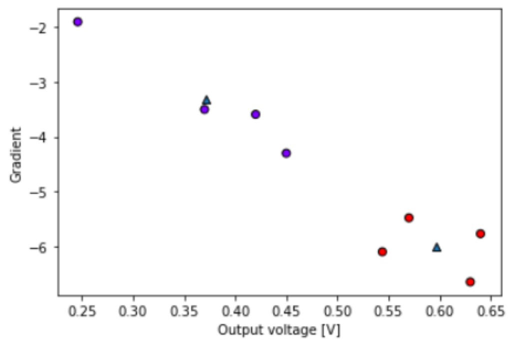


Fig. 13. Classification using the k-mean method. The inside sensor position was 15 mm.

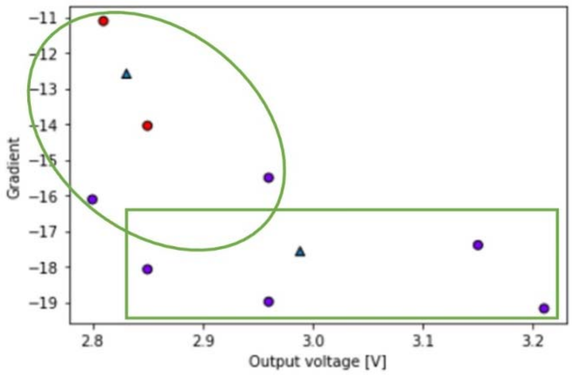


Fig. 14. Classification using the k-mean method. The inside sensor position was 50 mm.

4. Discussion

4.1. Sensor Position and Motion Limitation

Up to a sensor position of approximately 35 mm, the output voltage was larger when no restriction was applied than when a restriction was applied. This was probably because of the smaller kick of the foot during walking when restricted, and the foot was flat with the right foot landing evenly. The toe of the participant was positioned 40 mm from the base of the toes to the tips of the feet. Therefore, the toe sensor was closer to the outside and inside sensors at a position of 45 mm or more, such that the output was almost the same, irrespective of the limitation. This supported the case in which the output data from the sensors on the toe side varied considerably depending on the sensor position around the base of the toes. In contrast, minimal changes were observed when the toes were closer to the center of the foot. In addition, the range between the maximum and the minimum values increased when a restriction was applied because the landing of the foot at each time during walking varied.

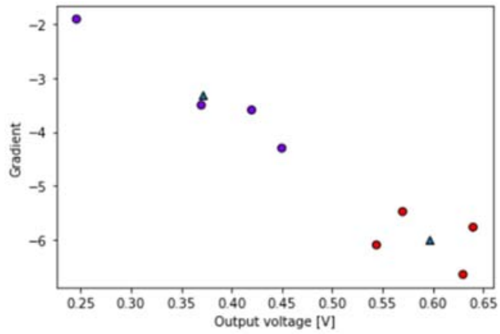


Fig. 15. Classification using the k-mean method. The heel sensor position was 50 mm.

Unlike sandals, shoes are less loose in the width direction, and the reduction is thought to be small because a commercially available insole is layered from the top. The reason for the large variation was that the shoe was loose in the length direction owing to the shape of the shoe, causing the position of the foot to shift in the length direction in the shoe when walking, and the toe area applied.

In the present example, the output voltage tended to increase closer to the heel end when no movement restrictions were applied to the sensor position at the heel. When exercise restrictions were added to the knee area, no difference was observed owing to flat feet. Therefore, the degree of ankle rotation could be detected.

4.2. Comparison of Two Types of Insole Sensors

By taking advantage of the ability to easily move the position of the sensor attached to the insole, we were able to study the differences in the output depending on the sensor position, that cannot be detected using commercially available insole sensors that have a fixed sensor position. This enabled to clarify the effect of the toe length on the sensor output. This also demonstrates the importance of the therapist in ensuring that the sensor was fixed exactly in the desired position. Sandals were chosen for this introductory experiment. However, the reproducibility must be improved by repeating the experiment regarding the dependence of the sensor position using shoes that are thought to have less deviation in the insole position.

4.3. Consideration of Classification Methods

Although the number of experiments conducted was small, we successfully demonstrated that decision tree classification based on the set of peak values and the steepest slope value in the decreasing portion after the peak could be used to classify the data into two groups. However, the boundary areas did not significantly differ. Thus, the amount of data must be increased, and a classification method such as a support vector machine must be considered.

The results showed that using the peak voltages of the toe, medial, and heel sensor outputs and the slope of the decrease after the peak as features in the SVM and decision tree analyses might be effective. Furthermore, the results obtained using the k-means method, which is an unsupervised learning method, suggested that classification using data from the medial and heel sensors was effective. As shown in Figs. 13, 14, and 15, the classification accuracies using the inside at 15 and 50 mm and heel at 50 mm were not considered high. The most accurate case was the sensor position of 50 mm; however, the cluster group contained different motion restrictions. Thus, we must obtain experimental results to improve accuracy.

5. Conclusions

The sensor position corresponding to the participant characteristics must be considered such that the therapist can obtain the desired data using an insole sensor. However, owing to cost constraints, features that consider variations in sensor positions must be selected. We observed that the optimization parameter of the classification candidate to select the better sensor position was the slope that indicated a decrease after the peak value. This result confirmed the increase in the experimental results.

Acknowledgments

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References

[1]. E. Anikina, L. Ivankina, I. Gumennikov, I. Kashchuk, E. Monastyrny, A study of World Older People at National Research Tomsk Polytechnic University, *Procedia Social and Behavioral Sciences*, Vol. 214, 2015, pp. 906-910.

[2]. E. Rudnicka, P. Napierala, A. Podfigurna, B. Meczekalski, R. Smolarczyk, M. Grymowicz, The world Health Organization (WHO) approach to health ageing, *Maturitas*, Vol. 139, 2020, pp. 6-11.

[3]. R. Baghezza, K. Bouchard, A. Bouzouance, C. G. Vallerand, From Offline to Real-time Distributed Activity Recognition in Wireless Sensor Networks for Healthcare: A Review, *Sensors*, Vol. 21, 2021, 2786.

[4]. J. D. Sciubba, Population aging as a global issue, in Oxford Research Encyclopedia of International Studies, *Oxford*, UK, 2020.

[5]. T. Jayawardhana, S. Anuththara, T. Nimnadi, R. Karadaanaarachchi, R. Jayathilaka, K. Galappaththi, Asian Ageing: The relationship between the elderly population and economic growth in the Asian context, *PLoS One*, Vol. 18, Issue 4, 2023, e0284895.

[6]. M. M. Alam, E. B. Hamida, Surveying Wearable Human Assistive Technology for Life and Safety Critical Applications: Standards, Challenges and Opportunities, *Sensors*, Vol. 14, 2014, pp. 9153-9209.

[7]. X. Qian, H. Cheng, D. Chen, Q. Liu, H. Chen, H. Jiang, M-C. Huang, The Smart Insole: A Pilot Study of Fall Detection, in *Proceedings of the Body Area Networks: Smart IoT and Big Data for Intelligent Health Management Conference (BODYNTES'19)*, 2019, pp. 37-49.

[8]. S. Subramaniam, S. Majumder, A. I. Faisal, M. J. Deen, Insole-Based systems for Health Monitoring: current Solutions and Research Challenges, *Sensors*, Vol. 22, 2022, 438.

[9]. S. Usmani, A. Saboor, M. Haris, M. A. Khan, H. Park, Latest Research Trends in Fall Detection and Prevention Using Machine Learning: A systematic Review, *Sensors*, Vol. 21, 2021, 5134.

[10]. A. G. M. Gaspar, L. V. Lapao, A digital Health Service for Elderly People with Balance Disorders and Risk of Falling: A Design Science Approach, *International Journal of Environmental Research and Public Health*, Vol. 19, 2022, 1855.

[11]. Y. Uchida, T. Funayama, Hori, M. Yuge, N. Shinozuka, Y. Kogure, Possibility of Detecting Changes in Health Conditions using an Improved 2D Array Sensor System, *Sensors & Transducers*, Vol. 259, Issue 5, 2022, pp. 29-36.

[12]. T. Funayama, Y. Uchida, Y. Kogure, Assessment of Walking Condition Using Pressure Sensors in the Floor Mat, in *Proceedings of the International Conference on Global Health Challenges*, Valencia, Spain, 2022.

[13]. Y. Uchida, T. Funayama, Y. Kogure, Possibility of Gait analysis with MediaPipe and Its Application in Evaluating the Effects, *International Journal on Advances in Life Sciences*, Vol. 15, 2023, pp. 44-54.

[14]. K. Fukushi, C. Huang, Z. Wang, H. Kajitani, F. Nihey, K. Nakazawa, On-Line Algorithms of Stride-Parameter Estimation for in-Soe Motion-Sensor System, *IEEE Sensors Journal*, Vol. 22, 2022, pp. 9636-9648.

[15]. S. Kim, S. Park, S. Lee, S. H. Seo, H. S. Kim, Y. Cha, J.-T. Kim, J,-W. Kim, Y.-C. Ha, J.-I. Yoo, Assessing physical abilities of sarcopenia patients using gait analysis and smart insole for development of digital biomarker, *Scientific Reports*, Vol. 13, 2023, 10602.

[16]. T. Funayama, Y. Uchida, Y. Kogure, Detection of motion restriction with smart insoles, *Sensors & Transducers*, Vol. 259, Issue 5, 2022, pp. 61-68.

[17]. T. Funayama, Y. Uchida, Y. Kogure, Step Measurement Using a Household Floor Mat and Shoe Sensors, *International J. of Advances in Life science*, vol. 15, Issues 1-2, 2023, pp. 33-34.
[18]. Y. Uchida, T. Funayama, E. Ohkubo, Y. Kogure, Difference in Sensor Placement Position of Insol-type Pressure Transducers, in *Proceedings of 9th international Conference on Sensors and Electronic Instrumentation Advance (SEIA'2023)*, Funchal, Portugal, 20-22 September 2023, pp. 40-43.
[19]. T. Funayama, Y. Uchida, Y. Kogure, D. Souma, R. Kimura, Feasibility of Gait Change Detection using Smart Footwears, in *Proceedings of 9th international Conference on Sensors and Electronic Instrumentation Advance (SEIA'23)*, Funchal, Portugal, 20-22 September 2023, pp. 60-63.