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Detection of Motion Restriction with Smart Insoles

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Abstract: In this study, a wireless smart insole was used to measure walking with joint motion restriction. This smart insole outputs data for four parts—toe, heel, inside, and outside—and the color of these parts changes according to the degree of weighting. Motion restrictions involving the ankle joint were performed to assess changes in the physical condition. Normal walking without motion restriction was also assessed. Raw data from the smart insole were graphed and visually predicted. Subsequently, we used support vector machines and K-means methods to detect the classifications. Analysis of the data with and without ankle joint restrictions showed a trend toward higher classification accuracy for those with restrictions. The peak value of each waveform during the gait cycle, rate of decrease in the value after each peak, and data inside the insole were identified as potential detection possibilities. The use of smart insoles may facilitate the determination of changes in physical conditions. This will lead to an assessment of the physical condition based on objective data.

Keywords: Smart insole, Physical condition assessment, Wearable devices, Walking monitoring, Wireless data.

1. Introduction

Assessing health conditions in daily life is beneficial for older people and those with health problems, and wearable devices are becoming increasingly popular as a form of healthcare. The feet are one of the most sensory-sensitive parts of the body, and as they are the only body part in contact with the floor when standing, they are responsible for correcting posture. Owing to their distance from the heart, blood circulation tends to be impaired during sitting and standing positions. The sole is the body part through which health conditions are likely to be indicated.

The indications of insoles for orthopedic diseases, including osteoarthritis, diabetes, and other ailments related to old age, are being investigated in the rehabilitation and health promotion fields [1–5]. The world is becoming an ageing society. As the population ages, the number of people facing health challenges will increase [6]. Therefore, having a healthy body and being active is important as long as possible. For this purpose, the assessment of activities will be useful. Research and development of smart insoles that can acquire digital data to assess the effects of aging and disease and for purposes such as fall prevention has also progressed in recent years [7–15]. The sensors used in these devices include acceleration, temperature, and pressure sensors [16–[24]. Considerable amount of data can be acquired from various sensors. Therefore, focusing on which data are valid and how they are needed is important to determine the health conditions of an individual [25]. We have previously conducted a study using smart insoles with occupational and physical therapists [26]. Occupational and physical therapists reviewed the response to smart insoles and studied their motor conditions, making observational judgments regarding the sensor responses of smart insoles during simulated motion restrictions. The response of the pressure sensor on the smart insole serves as objective and important data for rehabilitation. Herein, we examined the pressure sensor response of a wireless smart insole when walking with restricted ankle joints by simulating restricted motion of the upper and lower limbs to assess the changes in physical condition. The subjects' ankle joint range of motion was measured beforehand [27]. This study was approved by the Ethics Committee on Research of the Teikyo University of Science, with humans as participants.

2. Experimental Method

2.1. Device and Measurement System

The smart insoles used were a wireless type (FEELSOLE®) that measures four parts per foot and eight parts in total on both sides. Before the insoles can be used, they must be calibrated. Calibration was performed four times: no pressure with no feet in the shoes, standing on both feet, and standing on one foot on each side. A 10-s operation was possible. The colors of the four parts (toe, heel, inside, and outside) changed according to the weight applied. Therefore, the user can visually determine the differences in the application of weights to the four parts. The data were saved on an iPad Air (Apple) and could be viewed on the screen. They were transferred from the tablet to the PC via email and made available for analysis. The sampling frequency was 50 Hz, and the data were output in the CSV format.

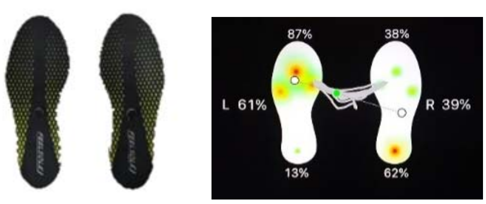

Fig. 1. Exterior of FEELSOLE and tablet screen.

2.2. Measurement Method

In this study, to assess changes in physical condition, simulated walking with restricted upper and lower limb motion was performed, and the pressure sensor response of the smart insoles was examined with and without restricted ankle joint motion focused. Ankle joint motion was simulated using a supporter. The responses of the sensors to the four regions of one leg and eight regions of both feet were examined. The ankle joint range of motion was measured in advance. The range of motion (ROM) of the ankle joint is shown in Table 1, where R signifies the right side, and L represents the left side. There were two subjects: a female in her 50s (Case A) and a male in his 70s (Case B).

Table 1. Ankle joint range of motion.

		Case A	Case B
Plantar flexion	**R**	50	45
	L	55	50
Dorsi flexion	**R**	20	20
	L	20	-5

2.3. Analysis Method

The characteristics were visually predicted by graphing the raw data from the smart insoles. Subsequently, with respect to the features, we studied how they could be classified as teaching data for machine learning, support vector machines (SVM), and we used the k-means method to check the degree of classification. SVM was performed with the Python library scikit-learn.

3. Results

3.1. Insole Data in Normal Condition

Figs. 2 and 3 show the data at the four insole regions when walking normally without restrictions in Case A. The four regions were the heel, toe, and inside and outside of the insole. The horizontal axis represents the data-measurement period. With respect to time, the number 500 on the graph represents 10 s. This corresponds to everything after Fig. 2. Figs. 2 and 3 show the right and left insoles, respectively.

The data values corresponding to the inside region have a left–right difference, with the right inside being larger than the left inside.

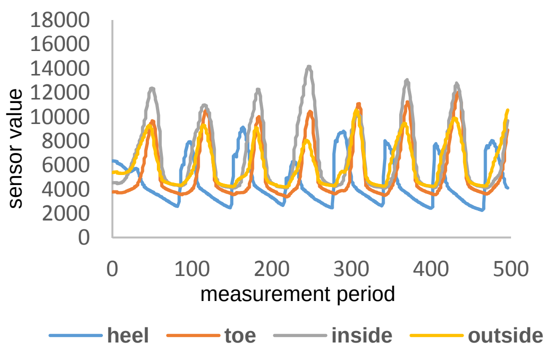

Fig. 2. Right insole with normal walking in Case A.

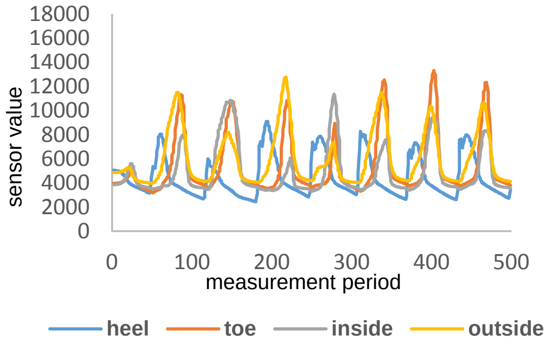

Fig. 3. Left insole with normal walking in Case A.

Figs. 4 and 5 show the data at the four insole regions when walking normally without restrictions in Case B. Figs. 4 and 5 show the right and left insoles, respectively.

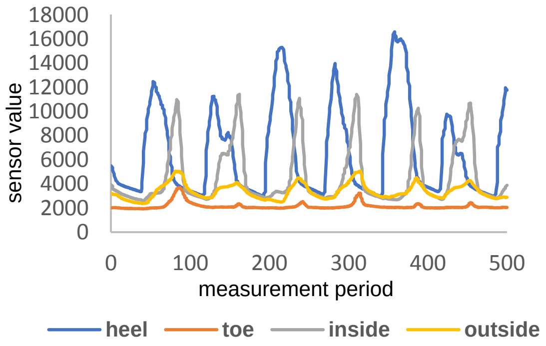

Fig. 4. Right insole with normal walking in Case B.

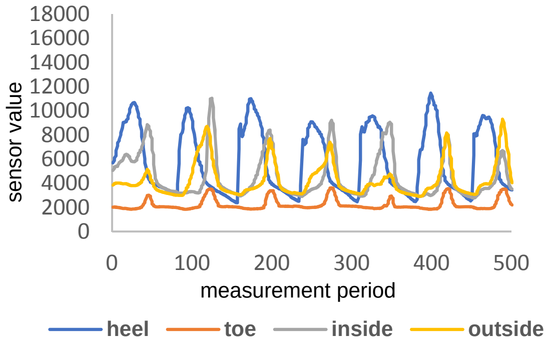

Fig. 5. Left insole with normal walking in Case B.

There were left–right differences in the data for all four regions, with particularly large left–right differences in the heel and outside region.

Even without the simulated motion restriction, there were differences from left to right and from condition to condition, even in the same case. For example, Case B showed larger heel data and a left–right difference, whereas in Case A, the heel data was small. The range of motion of the ankle joints is listed in Table 1. Case B has a larger left–right difference than Case A.

3.2. Insole Data in Ankle Joint Restriction

Figs. 6 and 7 show data from the right insole when the right ankle joint was restricted. Fig. 6 shows Case A, and Fig. 7 shows Case B.

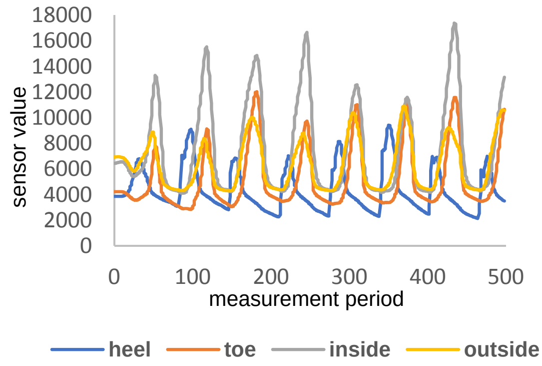

Fig. 6. Right insole with right ankle restriction in Case A.

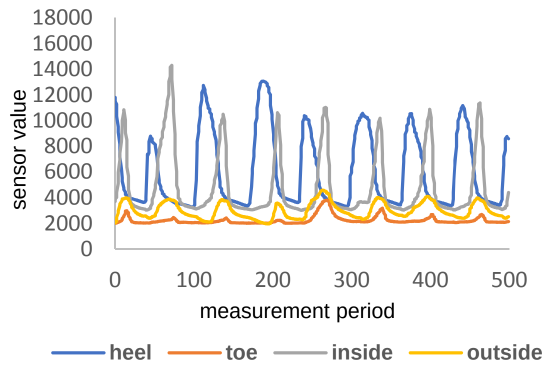

Fig. 7. Right insole with right ankle restriction in Case B.

Both cases changed from normal walking when the ankle joint was restricted. The differences with and without restrictions were greater at the heel in Case B and at the inside in Case A. Even for the inside in Case B, differences with and without restrictions were showed. In Case B, the waveform peak values for the outside and toe are lower and those for the heel and inside are higher, with and without restrictions. Decrease in value after waveform peak differed depending on ankle joint restrictions and insole regions.

3.3. Peak Value and Rate of Decrease

The peak value and rate of decrease of After the peak value in each waveform were analyzed. The rate of decrease was calculated using the least-squares method (LSM). The mean was calculated for each region of the right insole with respect to the percentage decrease after the waveform peak with and without right ankle joint restriction, as calculated using LSM. The rate of decrease corresponds to the gradient of the waveform. The absolute values of the mean for each region in Cases A and B are shown in Figs. 8 and 9, respectively. The vertical axis of the graph is the average of the Smart Insole data for each region. Walking without joint restrictions was considered normal.

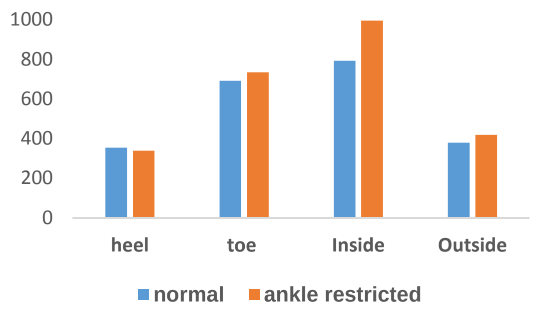

Fig. 8. Mean rate of decrease after waveform peak in Case A with and without restrictions.

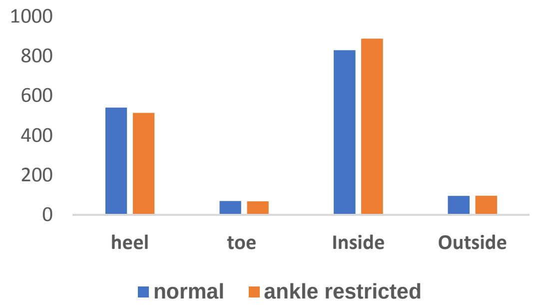

Fig. 9. Mean rate of decrease after waveform peak in Case B with and without restrictions

The data corresponding to the inside region were higher when there were restrictions in both cases, namely Cases A and B.

3.4. SVM Analysis Using Peak Values and Decreasing Rates

The possibility of classification by SVM was examined with respect to the peak and decrease rates of the right insole data with and without right ankle joint restrictions. Since this study was in its initial stages, we primarily focused on how the measured data can be classified. We will add new tests to confirm the accuracy of the classification in the future, however, in this study, we confirmed the possibility that SVM can be used to classify the data as supervised data. We conducted comparisons using LSM and Subtraction of two weighted average (SWA) in SVM. The rate of decrease in the waveform with SWA was calculated using a subtraction of the values before and after successive weighted averages to eliminate and smooth out abrupt changes. Among the subtracted values, the value with the largest decrease in value before and after, i.e., the rate of decrease, was extracted. The weighted average was obtained using five values (target value, two each before and after) calculated as follows. Owing to the large influence of the central region, the percentages were calculated by assigning 50% to the target value of the waveform, 20% to the values before and after one peak, and 10 % to the values before and after two peaks. SWA was calculated using the peak value and rate of decrease for each waveform. Since one dataset was used per wave, there were 6–7 data sets for each in the SVM. The SVM parameters were C = 10.0, the kernel was rbf, and gamma was 1×10^{-6}. This value was selected to the extent that it does not result in overtraining, although not fully optimized. All the subsequent SVMs used the same parameters.

A. Detection using inside and outside data

SVM analysis was performed using the peak value and rate of decrease data for each waveform as learning data and four types of teaching data: with and without right ankle joint restrictions, inside and outside of the right insole, and combinations of them. The results of SVM in Case A are shown in Figs. 10 and 11. Figs. 10 and 11 show LSM and SWA, respectively. The dots in the figure are black on the inside and red on the outside of the insole when the insole is normal without ankle joint restrictions and blue on the inside and white on the outside when the insole has ankle joint restrictions.

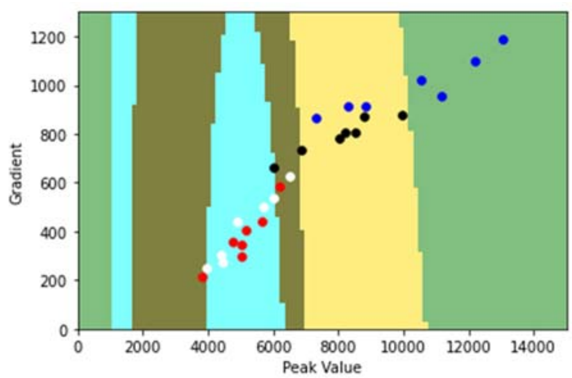

Fig. 10. SVM using LSM: inside and outside in Case A with and without restrictions.

In Case A, 60.7 % accuracy was obtained for LSM, as shown in Fig. 10, and 63.0 % for SWA, as shown in Fig. 11. Case B was also implemented using the same method as the SVM for Case A. Figs. 12 and 13 show LSM and SWA in Case B.

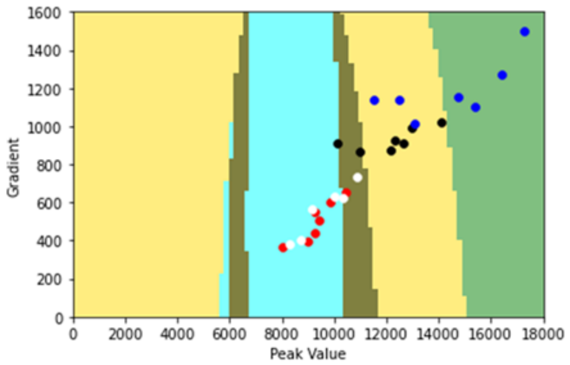

Fig. 11. SVM using SWA: inside and outside in Case A with and without restrictions.

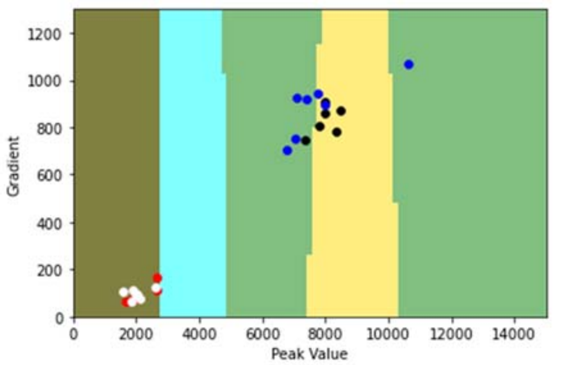

Fig. 12. SVM using LSM: inside and outside in Case B with and without restrictions.

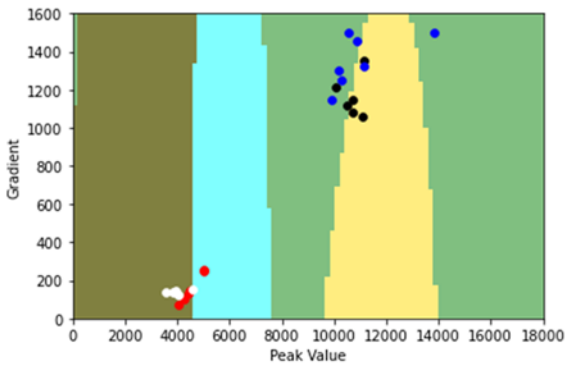

Fig. 13. SVM using SWA: inside and outside in Case B with and without restrictions.

In Case B, 65.4 % accuracy was obtained for LSM, as shown in Fig. 12, and 80.8 % for SWA, as shown in Fig. 13.

The accuracy was 60.7 % for LSM and 63.0 % for SWA in Case A and 65.4 % for LSM and 80.8 % for SWA in Case B. The results tended to be slightly more accurate for SWA than for LSM. The color of the dots indicates that more differences appear inside than outside when the ankle joint is restricted. This is shown in both Cases A and B.

B. Detection using heel and toe data

The heel and toe, which are considered points of attention in gait analysis, were analyzed. The peak value and decrease rate of the waveform were set as learning data, and SVM was performed with four types of data for teaching: distinction between the heel and toe of the right insole and the presence or absence of right ankle joint restrictions. Figs. 14 and 15 present Cases A and B. Results for the heel and toe are shown only for waveform peaks and the rate of decrease as calculated by SWA. The dots in the figure are black on the heel and red on the toe of the insole when the insole is normal without ankle joint restrictions and blue on the heel and white on the toe when the insole has ankle joint restrictions.

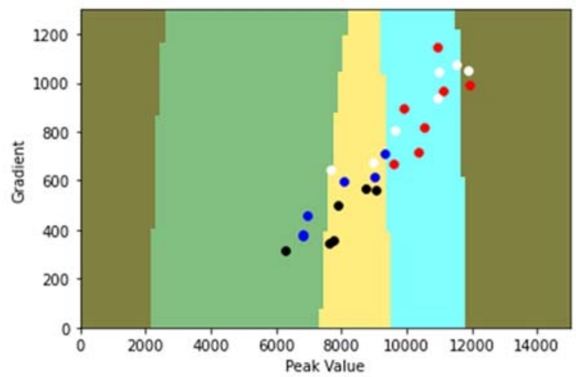

Fig. 14. SVM using SWA: heel and toe in Case A with and without restrictions.

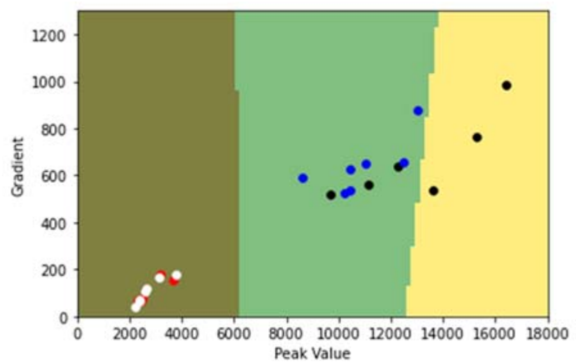

Fig. 15. SVM using SWA: heel and toe in Case B with and without restrictions.

Accuracy was 57.7 % in Case A and 65.4 % in Case B. These results were obtained using pairs of heel and toe data. While, regarding inside and outside pairs, they were 63.0% and 80.8%, respectively. Accuracy was higher for the inside and outside pairs than for the heel and toe pairs. Furthermore, the color of the dots in the figure indicates that although there is a difference between the heel and toe, detecting a difference owing to the presence or absence of restrictions is difficult.

C. Left and right insole data without restrictions

SVM analysis was performed on four types of insoles: left and right and inside and outside, when walking normally without joint restrictions. The waveform peaks and decrease rates calculated using the SWA are shown below. The results for Cases A and B are presented in Figs. 16 and 17, respectively. The dots in the figure are black for the right inside, red for the right outside, blue for the left inside, and white for the left outside.

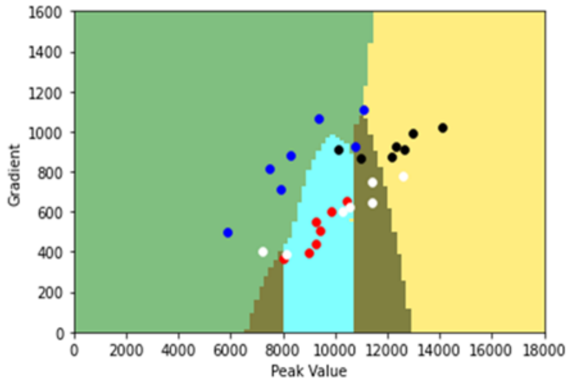

Fig. 16. SVM using SWA: inside and outside in Case A without restriction.

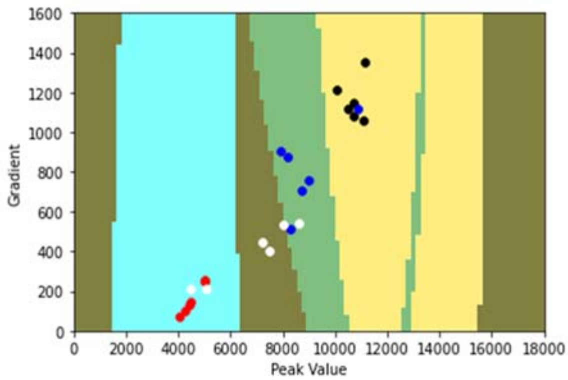

Fig. 17. SVM using SWA: inside and outside in Case B without restriction.

The accuracies were 67.9% for Case A and 79.2% for Case B. The colors of the dots in the figure also indicate that both Cases A and B tend to be classified into four categories.

SVM analysis was performed on four types of insoles—left and right, heel, and toe—when walking normally without joint restrictions. The waveform peaks and decrease rates calculated using the SWA are shown below. The results for Cases A and B are presented in Figs. 18 and 19, respectively. The dots in the figure are black, red, blue, and white for the right heel, right toe, left heel, and left toe, respectively.

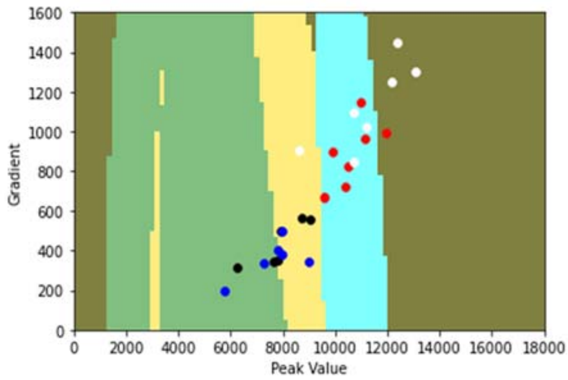

Fig. 18. SVM using SWA: heel and toe in Case A without restriction.

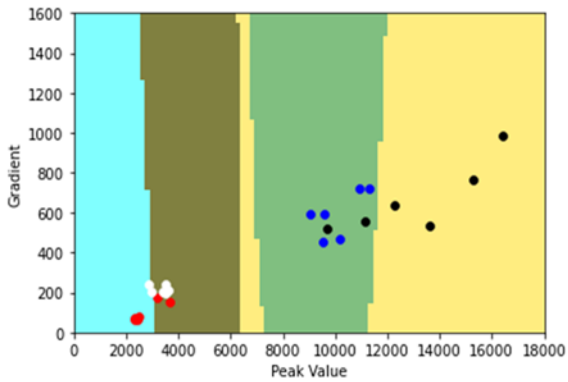

Fig. 19. SVM using SWA: heel and toe in Case B without restriction.

The accuracies were 57.7 % for Case A and 79.2 % for Case B. According to the colored dots in the figure, the trend is different between Cases A and B. Case A has higher values for the toes and Case B has higher values for the heels. Accuracy for the inside and outside of the insole was 67.9 % and 79.2 % for Cases A and B, respectively, which is equal to or better than that for the heel and toe.

3.5. Detection using K-means Clustering Method

The K-means clustering method was performed by inputting data for four patterns of combinations of inside and outside insoles, with and without ankle joint restrictions. The data were parsed using weighted calculated peaks and percentage reductions. This is unsupervised learning, which does not use information data on the insole parts and restrictions. Cases A and B were classified into four categories. However, for Case B, the centers of gravity of the two clusters are close. Figs. 20 and 21 show the results of the K-means method using SWA data for Cases A and B.

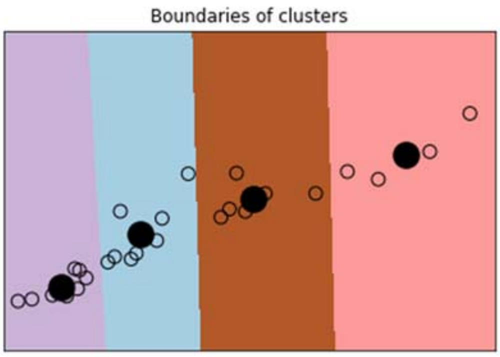

Fig. 20. K-means using SWA: inside and outside in Case A with and without restrictions

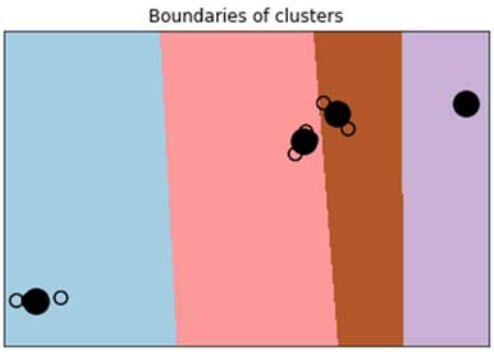

Fig. 21. K-means using SWA: inside and outside in Case B with and without restrictions

4. Discussion

The response to the smart insoles varied from left to right and condition to condition, even in the same case. However, the SVM classification, which simulates ankle joint restrictions, was more detectable for the inside and outside insole pairs than for the heel and toe pairs. This tendency was similar when discriminating between the left and right sides during normal walking, without restrictions. In addition, Case B, wherein the left–right difference in ankle joint range of motion was greater than that in Case A, had a higher accuracy by SVM analysis. With and without simulated ankle joint restriction, the rate of decrease inside the insole was higher for those with restriction from the colored points in the figure, that is, the inside of the unrestricted foot tended to change more slowly. However, whether these results apply to normal walking without restrictions remains to be investigated. The possibility that supporters or other factors may influence responses to smart insoles should also be considered.

According to studies already performed by occupational and physical therapists using the same smart insoles, they agree that the toes are considered important in terms of predicting motion restrictions and useful sensor parts. However, other aspects differed depending on the therapist. Smart insoles can be objectively applied and can complement therapists' assessments. In this study, we investigated the peak of each waveform in the insole data and the rate of decrease after the peak. The SVM analysis figure shows that the difference is particularly noticeable inside the insole. The inside and outside of the insoles are considered to be more difficult to assess by therapist observation than the heel and toes. In particular, the soles of the feet can be used not only to detect the subject's gait pattern but also to assess fatigue and other health conditions. Falls among older adults can also cause serious injuries such as broken bones and head trauma and may result in the need for nursing care. The use of smart insoles potentially makes the assessment of changes in physical conditions easier than ever before.

Therefore, we suggest that when assessing walking with smart insoles, three points should be considered in addition to examining the peak value and the rate of decrease after the peak: (1) the differences from the norm based on the characteristics of each individual case, (2) the response of the pressure sensor of the smart insole to common physical characteristics such as ankle joint range of motion and gait, and (3) the relation between the sensor and the sole of the foot.

5. Conclusions

In this study, we investigated two subjects with a walking time of 10 s using a small amount of data. We did not use machine-learning test data for the SVM. Therefore, the results of this study cannot be generalized. However, we did find the possibility that the data of the inside waveform peak and the rate of decrease can be useful. We plan to increase the number of subjects and extend the measurement time of the insoles.

Acknowledgements

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