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Possibility of Detecting Changes in Health Conditions using an Improved 2D Array Sensor System

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Abstract: For improved detection of changes in body conditions, herein, we propose a two-dimensional system, wherein sensors are placed parallel and perpendicular to the direction of walking, based on an already proposed system that employs pressure sensors. The sensors placed parallel to the direction of walking identify the foot that steps on the sensors, and two others pairs of sensors are placed at positions corresponding to the inner and outer sides of the left and right feet, respectively, to accurately detect the foot that steps on the sensors during walking. This improved two-dimensional health monitoring system is applied to a hemodialysis patient known to have a wobble problem before and after treatment. This is performed to obtain effective values as features for machine learning. Using data obtained from the additional sensors, we develop an index that can evaluate a patient's sense of balance. The results indicate that classification is possible based on the walking speed obtained from the pressure sensors installed orthogonally to the direction of travel and the devised balance index. Using these values, the K-means method, which does not use supervised data, can be used to classify the subjects into three regions, and it is demonstrated that changes in gait before and after hemodialysis can be detected, although at an early stage.

Keywords: Health monitoring system, Hemodialysis, Gait balance, Pressure sensors, Machine learning, and K-means method.

1. Introduction

The increase in elderly population is turning into a global concern, particularly in Asia. In particular, Japan is rapidly converting into a super-aging society. According to the 2020 population statistics [1], the percentage of the total population aged 65 years and older (the aging rate) was as high as 28.8 %, which is higher than the proportion of population aged 75 years and older, which is in turn higher than the proportion of population aged between 65 and 74 years. As the elderly population continues to grow, aging of hemodialysis patients is also emerging as a major concern. The number of hemodialysis patients is increasing annually. As of 2020, the average age for dialysis induction was 70.88 years, and the average

age was 69.40 years [2]. Furthermore, the post-treatment fatigue experienced by aging hemodialysis patients has become a significant problem, as staggering and falls often result in bone fractures, leading to inhibition of the daily living activities of bedridden patients [3-5]. In addition, this is often accompanied by a risk of falls in partially or totally blind patients with retinopathy, owing to diabetic nephropathy. Patients with physical conditions that change before and after hemodialysis require additional monitoring compared to patients with comparatively constant disabilities, such as motor paralysis and sensory disturbances. Several recent reports have revealed that the maintenance of lower-limb muscle strength is an effective preventive measure against the aforementioned conditions, and renal rehabilitation is often performed in accordance with the physical condition of patients [6]. In addition, several studies have reported on the use of dialysis and amino acid supplementation to minimize amino acid loss [7].

A major cause of unsteadiness among hemodialysis patients is decreased blood pressure owing to inappropriate dehydration rates. The relationship between blood pressure and cerebral blood flow is known to correlate with a decrease in mean arterial pressure and cerebral blood flow below a certain mean arterial pressure [8]. Thus, attempts have been made to prevent reductions in the blood pressure by monitoring decreased cerebral blood flow based on the leg blood flow. However, such attempts are limited to the prevention of falls by maintaining a patient's muscle strength and detecting a drop in blood pressure during dialysis [9]. Therefore, these attempts have not yet accomplished gait support or fall prevention after dialysis treatment.

The increase in the number of elderly people living alone is likely to become another major problem with the increase in the number of patients requiring medical treatment in today's hyperaged society. The World Health Organization has reported on the problem of falls among the elderly since 2014 [10]. In particular, falls affect one in three adults aged 65 years and older and 50% of adults aged 80 years and older each year. Compared to the citizens of other countries, the citizens of Japan have relatively poor social interactions with their neighbours and are surrounded by fewer older adults who are willing to assist them. Although the government is implementing concerted programs to prevent the elderly from becoming isolated, the current efforts are still inadequate.

Hence, several studies have investigated fall detection [11- 16]. A typical example of a monitoring facility involves the use of a surveillance camera and a microphone connected to a network. However, current surveillance camera systems are expensive and require an external power supply. Nevertheless, because these systems are equipped with cameras and microphones, they can respond to unusual movements or sounds or to situations when motion is undetected for a certain period. However, there exists a trade off between accuracy and personal privacy when dealing with imaging and sound technologies. For images, complex processing such as using avatars is possible and is acceptable in terms of monitoring. Although the amount of information may be inadequate, a system that detects changes in physical conditions by detecting movement in a room or other locations as a quantity has been reported previously.

Recently, a method for analyzing gait trajectories indoors using a capacitive proximity-sensing device, called Smart Floor, was reported [17- 18]. The Smart Floor is capable of capturing trajectories over 24 h. This system is capable of accurately recognizing multiple activities within the same indoor area using a lightweight algorithm. This is effective as capturing the walking trajectory of an elderly person living alone can be helpful in detecting falls or immobility, which may result from changes in physical conditions. However, it is often difficult to identify individuals when multiple people walk in the same space; hence, new algorithms should be developed explicitly for elderly households.

So far, several studies on fall detection have used accelerometers or smartphones to detect changes in physical conditions by detecting body tilts and foot movements while walking. These sensors are connected to a network, and a server or other device employs deep-learning technology to detect differences from the norm. However, power supply problems are likely to arise when operating such systems for an extended period. Because these services are often event driven, they can provide rapid responses if used at institutions. If an incident occurs at home or in a remote area, the benefit of reporting the incident is clearly significant; however, this system lacks when an immediate response is required. Thus, current systems in Japan are lacking in terms of the foregoing.

We have proposed a simple monitoring system employing a flexible pressure sensor to enable long-term measurements. Further, we report the differences in data using machine learning analysis methods, such as support vector machines (SVM) and decision trees. Although this study involved activities that included rising from a bed and walking a few steps, it demonstrated the existence of a movement pseudo-limitation and the possibility of distinguishing between two people [19- 21]. In this study, we examined whether the proposed system could detect differences in the balance and walking speeds of patients undergoing dialysis treatments by obtaining these variables before and after dialysis treatments, which is assumed to be a time when changes in physical condition are more likely to occur [22].

2. Experiment

2.1. Subjects

The study subjects were six maintenance dialysis patients undergoing dialysis therapy at the Katori Omigawa Medical Center. Described next are certain patient characteristics: age range of 64–91 years, average dialysis history of 102.5 ± 725.5 months, and the primary diseases were diabetic nephritis in five patients; however, one patient had nephrosclerosis. In addition, two of the subjects had visual impairment in both eyes owing to diabetic retinopathy and optical valves, and two patients were suspected to have lower extremity peripheral artery diseases based on the ankle brachial pressure index. Furthermore, a male subject in his 60s, who had not received hemodialysis treatment, was evaluated at a university laboratory as a reference.

The study design and protocol were reviewed and approved by the Ethics Committee for Human Subjects Research of Teikyo University of Science and the Ethics Committee of Katori Omigawa Medical Center. A written informed consent for participation in the study and publication of the study results was obtained from all study participants.

2.2. Overview of the New System

The improved 2D health monitoring system, as depicted in Fig. 1, had two pairs of position-detection sensors, one for each foot, which were placed parallel to the direction of walking; this arrangement is in contrast to the conventional perpendicular arrangement of sensors, represented by P. For example, eight sensors were placed to detect whether a weight was placed on the inner or outer side of the left foot, with even and odd numbers as subscripts, such as Q0 and Q1. These sensors were placed 1.5 cm apart so that the inner and outer sides of the foot could be detected. As the length of the sensors was only 62 cm, two sets of sensors were placed in series so that a length of approximately 120 cm could be analyzed. Considering a particular subject's physique, the distance between the left and right feet was assumed to be approximately 15 cm. For sensors placed perpendicular to the direction of travel, only the distance between P0 and P1 was assumed to be 10 cm at the starting point, and the distance thereafter was 15 cm. The sensors were affixed using a tape on a plastic sheet to highlight their positions, and the surface was protected using another plastic sheet. Figure 2 presents an image of the proposed system.

The configuration of the proposed system is presented in Fig. 3. A pressure sensor similar to a previously reported one was used in this study, and the resistance values varied from 100 Ω to 1 MΩ, depending on the pressure. A 1 kΩ resistor was connected in series with the sensor, and the voltage change of the resistor was employed as the input signal. Each sensor measured the voltage at a frequency of 1 kHz. The signals from 16 sensors were examined in pairs using a program created in Processing3 by connecting a personal computer (PC) and an Arduino Mega2560 R3. Considering the communication and write times, 50 pairs of data were acquired per second. The output signals obtained from each pressure sensor were imported to the PC as text data and processed using Microsoft Excel and Python. The definitions of the output pulses used in the analysis are depicted in the figure.

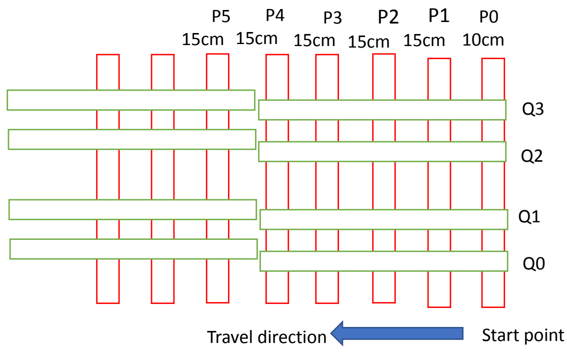

Fig. 1. Improved 2D health monitoring system.

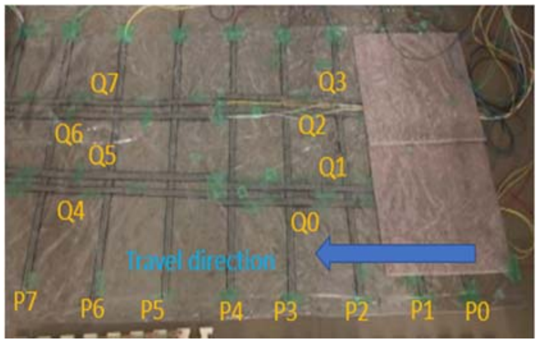

Fig. 2. Photograph of the system.

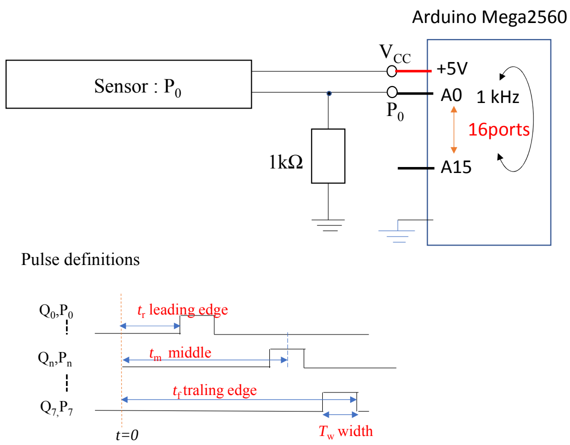

Fig. 3. Detection of output signals.

2.3. Measurement Method

The measurement interval between the two pairs of foot sensors had to be adjusted to match the motion interval between the subject's left and right feet; however, in this case, the measurement was not optimized for each individual patient as multiple participants were considered. Therefore, the waveforms of the inner and outer feet of the left and right feet differed from subject to subject. Because focusing too much on the pressure sensor during walking could result in significant differences from the natural gait, we verbally instructed the subjects to walk only in the direction of the sensor parallel to the direction of gait.

3. Results

Fig. 4 presents the gait data of the reference subject obtained from a preliminary experiment. The upper figure depicts the positional relationship between the sensors and the feet, the middle figure presents the output signal obtained from the sensor positioned parallel to the direction of gait, and the lower figure presents the signal obtained from the sensor positioned perpendicular to the direction of gait.

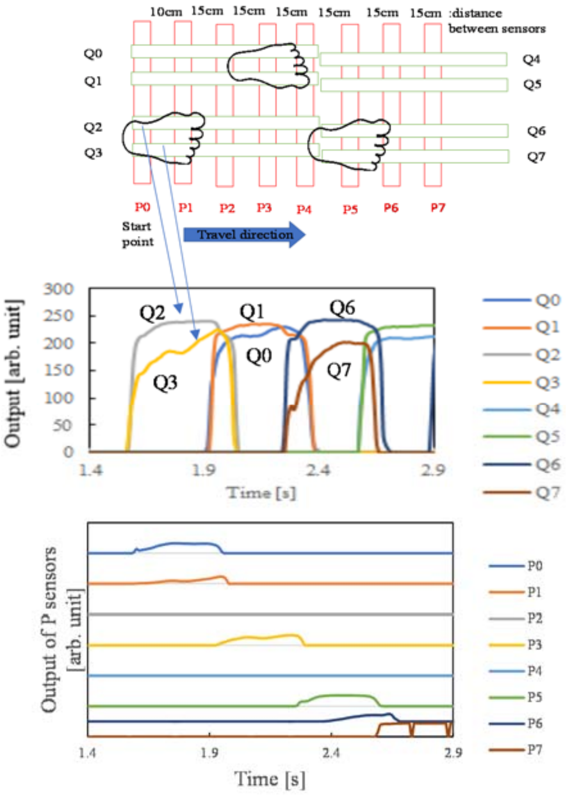

Fig. 4. Output waveforms of sensors Q and P corresponding to the sensor and foot positions, respectively; the upper figure shows the sensor and foot position, the middle figure shows the waveform of Q, and the lower figure shows the wave form of P.

The two sensors, labeled Q2 and Q3, detected the pressure applied to the outside and inside of the right foot, respectively. The waveforms illustrated in the middle panel of Fig. 4 represent signals that are produced in response to the motions of the outer and inner sides of the left and right feet, respectively. Differences in the shape of the rise in waveforms were also observed. The P-sensor signal corresponding to the walking direction, depicted in the lower part of Figure 4, presents the waveforms corresponding to the left and right feet; however, the amount of data is inadequate. Notably, machine learning, through the accumulation of data, can facilitate the identification of individuals.

An example of the data obtained from a subject undergoing hemodialysis is shown in Fig. 5. Compared to the subjects not undergoing hemodialysis, several cases with no signals after hemodialysis were obtained from the sensor represented by Q and the imbalance; however, a simple comparison is difficult owing to the ages of patients and differences in measurement locations.

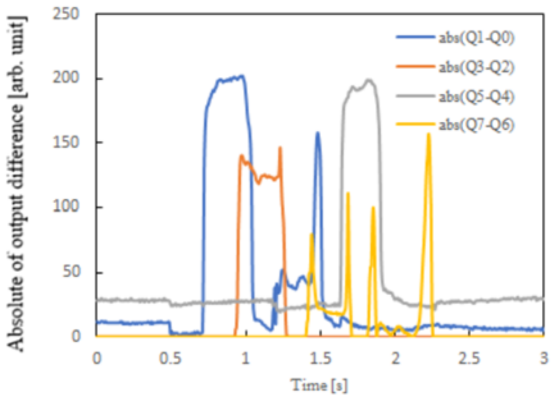

Fig. 5. An example of data from a subject undergoing hemodialysis.

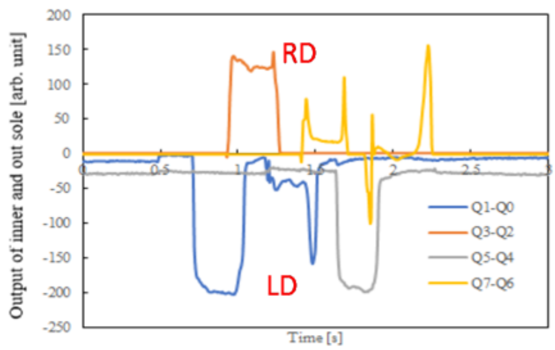

Fig. 6. The waveforms showing the difference in output between the inner and outer foot.

The waveforms highlighting the differences between the medial and lateral outputs obtained from the waveforms depicted in Fig. 5 are shown in Fig. 6. The amplitude of the outer signal was greater than that of the inner signal for both the left and right feet. Similarly, the waveforms corresponding to the first and second steps of the left foot had different amplitudes; however, the shapes were similar. In addition, the waveforms corresponding to the first and second steps of the right foot had different amplitudes and similar shapes. These results indicate that it may be possible to distinguish between the right and left feet by identifying the signal difference between the inner and outer feet. However, the classification is difficult using the output difference waveform. We noticed that the left and right feet alternately stepped on the sensor, and a spike-like output was observed as the weight shifted from the left foot to the right foot and the left foot left the sensor. In addition, we discovered that the classification based on the output difference waveform was difficult.

Note that the balance of a subject is deemed to be good if the difference between the total time that the right foot is on the sensor and the total time that the left foot is on the sensor is equal, and total time is zero. From this figure, we attempted to evaluate the difference in the duration for which the right and left feet stepped on the line; however, we could not classify the subjects accordingly.

To classify the data presented in Fig. 6, the sum of the differences between each left and right feet was defined as follows. The sum of the medial and lateral differences of the left foot, Q1–Q0 and Q5–Q4, was expressed as LD, and the sum of Q3–Q2 and Q7–Q6 was expressed as RD. We attempted to plot the absolute values of LD and RD in two dimensions using the obtained values. The corresponding results are depicted in Fig. 7. If the difference between the times at which the right foot and left feet stepped on the sensor was similar, the balance of the subject was deemed to be good. Therefore, we attempted to evaluate the subjects based on this difference in times; however, we could not classify the subjects accordingly.

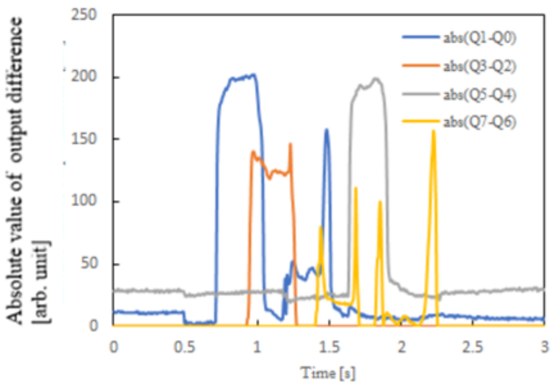

Fig. 7. Aggregate results of the absolute value of the left and right time difference.

Fig. 8 presents the results obtained by analyzing the data using a linear classification of SVMs, with LD and RD as the feature values; this was done because the waveforms corresponding to the movements of the left and right feet were repeated nearly in a similar manner. The support vector analysis classified nearly two areas; however, where LD was small and RD was large, an overlap was noted in certain areas circled by ovals.

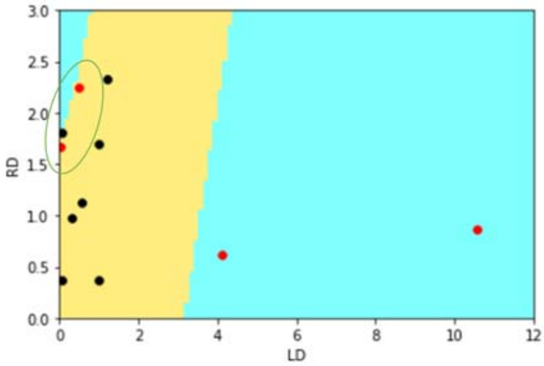

Fig. 8 SVM classification using LR and RD.

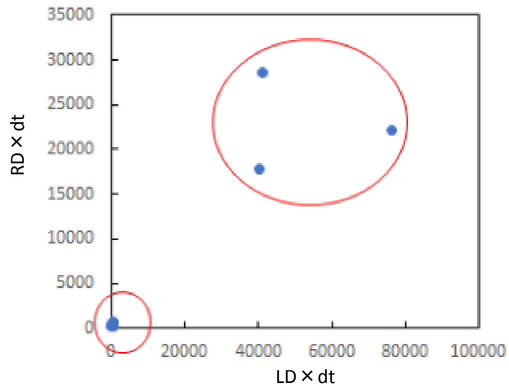

Fig. 9 The product of signal intensity and time dt from each of the left and right inner and outer feet.

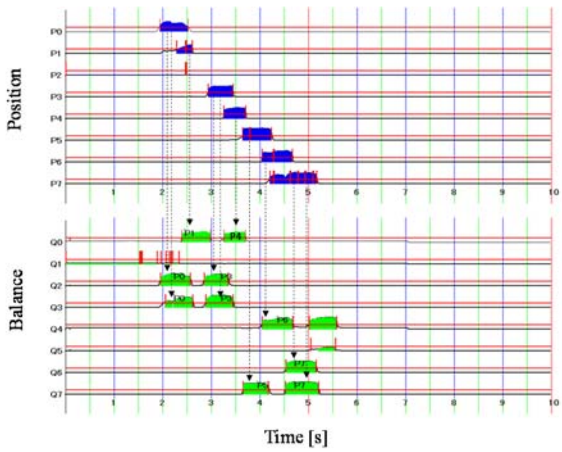

Fig. 10. Identification of the left and right feet that stepped on the sensors.

Next, the product of the signal strength and time dt measured from the inside and outside of each of the left and right feet, respectively, was obtained as an area and was plotted in two dimensions, as shown in Fig. 9. Eight points were clustered near the origin, and the other three points were far apart and could be treated as features. However, detailed examination of the subjects at each point could not provide any evidence regarding the symptoms.

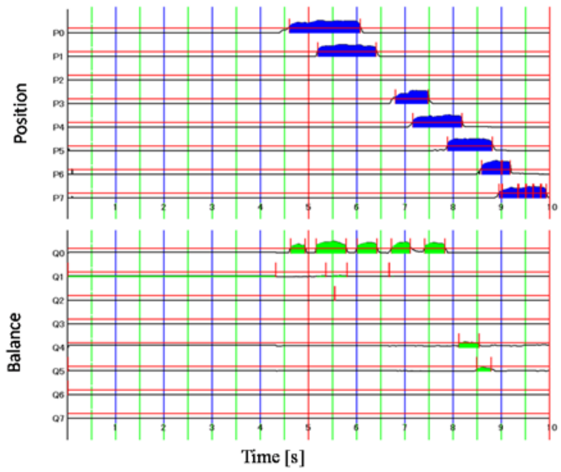

Fig. 11. Example of unbalanced measurement.

Fig. 10 presents the output signals obtained using the proposed system. The gait speed was obtained from the data collected from the P-sensor signals. The foot (left or right) that stepped on the sensor was identified by searching for the Q sensor that responded simultaneously to the signal depicted in Fig. 10, which corresponds to position P. The left and right feet alternated; however, some points could not be identified.

In the example presented in Fig. 11, the output signal progresses at almost constant intervals with respect to the direction of travel. In contrast, the Q signal, which indicates poor balance, can only be partially observed, indicating that it is moving to the left with respect to the direction of travel. This was confirmed based on the observations reported by the person who performed the measurement on that day, which indicates that the sensor was not stepped on properly.

Table 1 summarizes the measurement results depicted in Fig. 10, including the differences in the rise time and pulse width of the output signal obtained from the sensor and the results on the identification of the foot that stepped on the sensor. The results indicate that the right and left feet alternately stepped on the P sensor corresponding to the position. Because a variation was noted in the pulse width of the signal, we calculated the walking speed based on the rise time. The data collected from nearly all subjects indicated that the elapsed time and distance corresponding to each sensor position were nearly proportional to each other.

We observed that the gait speed before and after hemodialysis differed significantly among the subjects. Thus, using the walking speed as a new feature may be effective. We concluded that the reaction time of the sensor and the product of the time when the subject stepped on the sensor and the output voltage could not be used for effective classification of the left–right balance, and hence, is essential to consider another index.

Table 1. List of position sensor rise time and data on which foot is stepping on Pn, left or right.

Senor	Leading tr[s]	Tarling tf[s]	Middle tm[s]	Width tw[s]	L or R
P0	1.94	2.52	2.23	0.58	R
P1	2.29	2.61	2.45	0.32	L
P2	NA	NA	NA	NA	
P3	2.94	3.45	3.2	0.51	R
P4	3.26	3.71	3.49	0.45	L
P5	3.65	4.24	3.95	0.59	R
P6	4.05	4.67	4.36	0.62	L
P7	4.21	5.17	4.7	0.96	R

Based on these results, the numbers of steps nL for the left foot (L) and nR for the right foot (R) were obtained. The balance index is defined as follows:

$$|\Delta n|/n=|nL-nR|/(nL+nR). \quad (1)$$

The walking speed, number of times that the left foot stepped on the sensor, number of times that the right foot stepped on the sensor, and wobble coefficient defined in this study for all subjects are shown in Table 2.

Based on the relationship between the gait speed and balance index |Δn|/n, the data could be classified into two areas using an SVM method as shown in Fig. 12. However, the data with greater values of gait speed were separated from each other and could not be sufficiently classified; hence, further analysis is essential. We hypothesized that this could be attributed to the fact that the classification results obtained by the measurer could have been problematic and considered applying the K-means method, which does not provide supervised data.

Table 2. Wobble coefficient defined in this study for all subject.

Sample No	v (km/h)	nL	nR	$\lvert \Delta n \rvert / n$
1	1.44	3	4	0.143
2	1.245	3	0	1
3	3.112	1	2	0.333
4	1.859	5	2	0.429
5	1.286	3	2	0.333
6	0.873	6	0	1
7	1.507	3	4	0.143
8	2.878	2	1	0.333
9	1.34	3	5	0.286
10	0.487	1	7	0.857
11	1.294	4	0	1

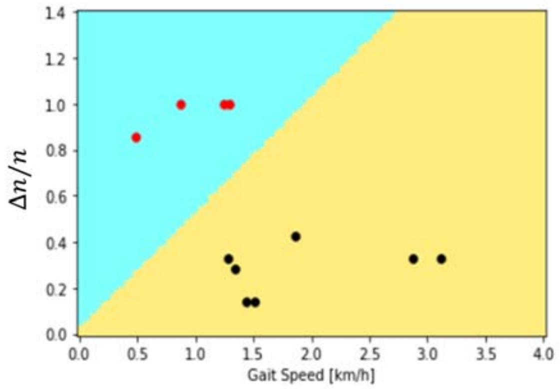

Fig. 12. Classified by the SVM methods.

As shown in Fig. 13, the pre- and post-hemodialysis balance indexes and gait speed data were classified into three clusters using the K-means method, reflecting the pre- and post-hemodialysis states of the subject. Here, triangular symbols represent the center of gravity for each cluster.

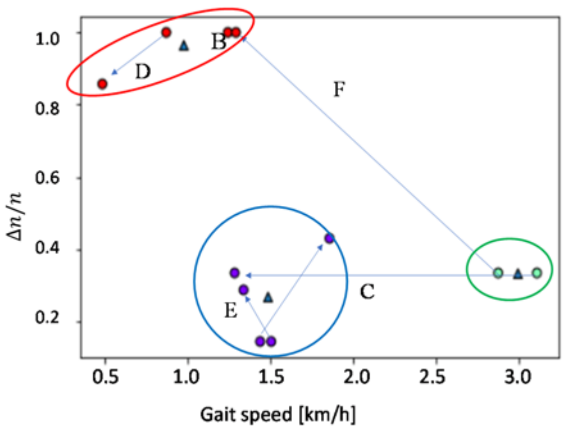

Fig. 13. Classified by the K-means methods.

4. Discussions

A flexible pressure sensor was used in the measurement considered in this study and enabled an objective evaluation of the severity of the changes in physical conditions by analyzing the measurement results of foot contact pressure during walking and the balance between the inner and outer contact pressures on the left and right sides, respectively. Further, we examined the possibility of clinical application of this system by examining several cases of individual subjects and selected subjects who were elderly (D), visually impaired (B, C), or had excessive water removal (C, F). The corresponding details are presented separately in this paper. We measured the blood flow in the lower limbs before and after dialysis as an indicator of post-dialysis staggering and related the results of the pressure sensor analysis to the effects of water removal and blood pressure decrease during dialysis. The pressure sensor results revealed that in all the subjects, a decrease in the walking speed and walking balance was noted immediately after dialysis. In addition, all subjects presented a decrease in lower-limb blood flow, indicating a relationship between the decrease in lower-limb blood flow and staggering to certain extent. These results suggest that the analysis data obtained using this system can detect changes in physical conditions based on the background and dialysis conditions of a patient and provide appropriate feedback to medical staff and family members on care appropriate to the condition of the patient.

5. Conclusions

Herein, we conducted an analysis based on an improved pressure sensor system on subjects undergoing hemodialysis treatment and adopted machine learning using the K-means method; further, we obtained the gait speed and balance index. Consequently, we proposed a system that could possibly detect changes in the physical conditions of patients after dialysis.

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