Step Measurement Using a Household Floor Mat and Shoe Sensors

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***Abstract*—Recently, many healthcare devices have been developed to monitor the health conditions of older people and others with health problems. To detect even the slightest changes in physical condition, it is crucial to carry out assessments during long periods of time while people are engaged in their normal daily activities, which do not change from usual. However, while devices to assess health conditions are beneficial, they also present challenges, such as invasion of privacy by monitoring systems, difficulty in operation, and handling of large amounts of data. Walking is sometimes referred to as the sixth vital sign, and is used to assess various diseases, including central nervous system, orthopedic, cardiovascular and respiratory diseases. Research on the development of smart insoles that can acquire digital data is increasing. However, smart insoles cannot be used at home in cultures in which shoes are not worn at home. To overcome these challenges, we have developed a gait assessment device that integrates pressure sensors into a floor mat for daily use. The purpose of developing this device is not to analyze gait improvement, but to capture changes in physical condition in daily living activities through changes in walking. The equipment comprises a grid of eight pressure sensors, each perpendicular and parallel to the walking direction. Because this floor mat is intended for use in homes, the measurement distance is shorter compared to conventional gait assessments. Therefore, we study the possibility of floor mats via the timed up and go (TUG) test, a conventional walking assessment method, and shoes fitted with pressure and acceleration sensors. Three subjects performed free walking, walking with an older people experience set, and walking with ankle and knee joints restricted by supporters. In addition to simulated motions and visual limitations, comfort walking and fast walking were also performed and examined. The obtained results indicate a high correlation between insoles with pressure sensors and floor mats relative to step time, thereby suggesting the usefulness of floor mats.**

Keywords-Walking Assessment; Floor Sensors; Smart Shoes; Activities of Daily Living; Health Care.

I. Introduction

We have been performing studies to capture changes in health conditions during daily life activities with digital measuring instruments [1]. These studies are conducted by an interdisciplinary team consisting of occupational therapists, physical therapists, human-machine interface experts, physicists, medical doctors, and others [2]. We have been suggesting the importance of assessments of everyday life [2]–[4]. However, it is not easy to make a routine health assessment actions on your own. Activities of daily living such as eating, changing, dressing, toileting, and bathing involve the use of various items, such as dishes, clothes, toothbrushes, and toilet seats. By incorporating sensors that can measure these activities, rehabilitation assessments can be made easier. Optical, acceleration, and pressure sensors are useful tools for rehabilitation assessment of activities of daily living. Floor mats are frequently used every day, making it easy to detect changes in activity. Walking is sometimes referred to as the sixth vital sign [5], and assessments of soles and walking have a high potential for understanding health status. Gait measurements using smart insoles with pressure and acceleration sensors have high accuracy; however, in areas where there is no culture of wearing shoes indoors, measurements cannot be taken indoors.

The population of the world is aging, which has led to an increase in the number of people facing health problems [6]. Therefore, having a healthy body and being active are important for as long as possible. For this purpose, an assessment of the activities will be useful. Gait assessment can be an indicator of overall health as well as lower extremity disease. Walking assessment is used for various patients, including older people [7]–[16], and to assess various disabilities, central nervous system diseases such as cerebrovascular disease, Parkinson’s disease, multiple sclerosis [17]–[24], cardiovascular and respiratory diseases [25]–[27], orthopedic diseases such as back pain [28], cognitive dysfunctions [29,30], and others [31]. Recently, several monitoring support equipment and systems for older adults and those with health problems have been researched, developed, and marketed [32]–[38]. The use of this type of equipment is becoming an important method of health support. Wearable devices for assessing health conditions are becoming increasingly popular in the healthcare field. Digital devices are also being used to evaluate gait, [39]–[45] and the research and development of smart insoles for aging, disease assessment, and fall prevention is increasing [45]–[48]. While beneficial, these types of equipment also present problems, such as invasion of privacy by the monitoring system, difficulty in operation, and handling large amounts of data. Health conditions are often detected through vital sign measurement and movement monitoring. The sensors used in these devices include infrared, acceleration, temperature, and pressure sensors [40].

Long-term assessments during normal daily activities are important for monitoring even slight changes in health. The assessment of walking during dual tasks, when attention is focused on activities other than walking, is considered important for understanding life risks. The environment and comfort level vary between a laboratory or hospital and their homes, and their health conditions can change throughout the day. Therefore, it is crucial to conduct ongoing and long-term assessments in the home environment, where people spend their everyday lives, rather than relying solely on evaluations conducted in hospitals or medical facilities. By incorporating sensors into items used in daily life, assessments can be performed for extended periods at home. However, because a large amount of data is collected over a long period, it is important to focus on which data is effective and how it is needed to determine an individual's health conditions [46]. In addition, to eliminate invasion of privacy, it is useful to turn measurements on and off at one's will; however, this requires the operation of the device. Older people or disabled users are required to be able to use the device in their daily lives. However, it is not easy to habituate device operation for healthcare in daily life. Self-care equipment should be beneficial, easy to operate, convenient, and practical for older people and those with disabilities who face health challenges. In addition, it is important that healthcare professional supporters are able to understand and utilize the meaning of the data.

Therefore, we developed gait assessment equipment that incorporates a pressure sensor in a floor mat used in daily life [49]. The floor mat is expected to measure a person's movement speed in their daily life without being turned on or off. The two key points of this equipment are privacy protection through a floor mat and the ability to understand health conditions without measuring vital signs. We previously used this device to study hemodialysis patients [40]. The conventional assessment methods used in rehabilitation, including the timed up and go (TUG) test, do not assess activities of daily living that are repeated daily. Digital measuring devices for daily activities can increase the measurement interval and amount of measurement data. The measurement accuracy was also improved, making it easy to compare the data we obtained with past data. This is not just a digitalization of the conventional rehabilitation assessment methods. This floor mat is designed for daily household use and is shorter than conventional gait assessments, such as TUG test; however, it can increase the measurement interval. The time per step can also be measured. Gait measurement is highly accurate with smart insoles with built-in pressure and acceleration sensors; however, in areas where there is no culture of wearing shoes inside the home, it is not possible to measure gait inside the home.

This report studies step measurement on a floor mat with built-in sensors that can be used in daily life and examines the potential use of the floor mat by comparing it with the TUG test, a gait assessment method, and smart shoes. Three subjects wore an older people experience set that simulated motor impairment and performed fast and comfortable walking on the TUG test and floor mats to determine the usefulness of the floor mats and speed calculation formula [1]. The same three subjects then walked and took measurements on the floor mat wearing shoes with acceleration and pressure sensors attached, with the knee and ankle joints restricted by the supporters. The step time, step length, and speed were compared between the floor mat and shoe-worn sensors. The characteristics used by occupational therapists to judge gait measurement in activities of daily living were also examined.

This study was approved by the Ethics Committee on Research with Humans as Subjects of Teikyo University of Science. Section II describes the experimental method, Section III describes the results, Section IV presents a discussion, and Section V presents the conclusion.

II. Experimental Method

A. Devices and Measurement Systems

1) Floor mat

The study used a floor mat with a grid array of 16 pressure sensors. Eight sensors (P0–P7) were perpendicular to the walking direction, and eight sensors (Q0–Q7) were parallel to the walking direction (see Figure 1). The perpendicular sensors were 10 cm apart only at the initial P0–P1 sensor interval and 15 cm apart at the other sensor intervals.

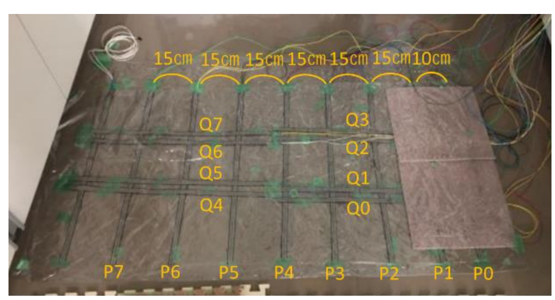

Figure 1. Floor mat-type equipment with pressure sensor array.

The parallel Q sensors were in pairs, two pairs in the front and two pairs in the rear, with each pair approximately 15 cm apart. The length of the sensor was

62 cm, and it measured approximately 120 cm in the direction of walking. The equipment size allows its use and placement at home. A clear plastic sheet protects the surface so that the sensor position can be checked. The sampling frequency of the equipment was 100 Hz. The approximate cost required for the creation of this floor mat is approximately 215 US dollars, with 16 sensors costing 180 dollars at 11 dollars each and one Arduino costing 35 dollars.

2) Insole with Pressuresenors

The smart insoles used were of a wireless type (FEELSOLE®) that measured four parts per foot and eight parts in total on both sides (see Figure 2). The insoles must be calibrated before they can be used. 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 applied weight. The video was also recorded, and the video and pressure sensor data from the smart insole were synchronized. The data were saved on an iPad Air (Apple) and could be viewed on a screen. They were transferred from the tablet to a PC via email and made available for analysis. The sampling frequency was 50 Hz, and the data were output in CSV format.

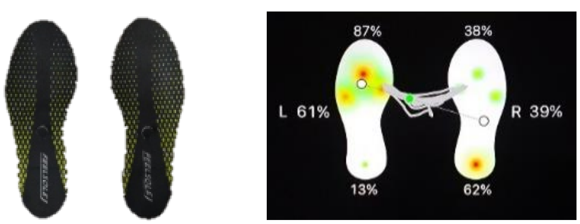

Figure 2. Exterior of FEELSOLE and tablet screen.

3) Accelerometer with Shoe Adhesion

The accelerometer used was the ORPHE CORE® (see Figure 3). It was measured using the iPhone application ORPHE TRACK®. The ORPHE TRACK® app and ORPHE CORE® connect wirelessly via Bluetooth. The data were uploaded to the cloud through the app and could be confirmed in CSV format every minute with ORPHE TRACK®, analyzing steps, distance, stride, step speed, pronation, impact angle, cadence, landing force, and contact time. The sampling frequency was set to 200 Hz. The video was not synchronized; therefore, comparison with the data of each step on the floor mat was impossible. The assessments were carried out with the device attached to the outside of the shoe and with it installed in the insole.

Figure 3. Accelerometer ORPHE CORE.

B. Walking measurements and Analysis Methods

1) TUG test and walking on floor mat

a) Walking measurements

Three subjects in their 50s to 70s (Cases A, B, and C) performed the TUG test and walked on the sensor array floor mat under a simulated restricted motion while wearing the older person experience set (see Figure 4).

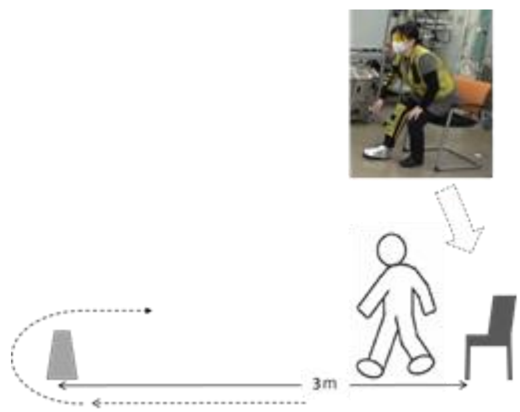

Figure 4. Timed Up and Go test.

The TUG test measures the time it takes to get up from a chair, go around a cone 3 m away, walk back to the chair, and sit down. The time taken was measured. The TUG test is often used in walking assessment during rehabilitation. Walking assessment is important for maximal walking speed (MWS) and self-selected walking speed (SSWS). Thus, we performed the test not only with comfortable walking, which is a standard practice, but also with fast walking. The motion restrictions varied by the subject. Participant A wore tinted eyeglasses in addition to (1) trunk-weighted and left upper and lower limb restrictions, followed by (2) trunk-weighted and right upper and lower limb restrictions. Subject B was (3) weighted on the trunk and had both legs restricted. Subject C was (4) weighted on the trunk. The subjects then walked on the sensor array floor mat without any motion restrictions. Videotaping and ankle joint range of motion (ROM) measurements were also conducted by an occupational therapist. The ROM of the ankle joint with plantar flexion and dorsiflexion is shown in Table I. R and L represent the right and left sides, respectively.

TABLE I. RANGE OF MOTION FOR CASES A, B, AND C

		Subjects		
Direction of Motions	**R / L Side**	Case A	Case B	Case C
plantar flexion	R	50	60	45
	L	55	50	50
dorsi flexion	R	20	10	20
	L	20	5	-5

b) Analysis

Figures 5 and 6 show examples of graphical representations of the output data for P0–P7 and Q0–Q7, respectively. For the least-Squares Method (LSM) calculation, data over half the height of the highest signal were used. In addition, data with very few continuous signals were judged to be noisy and were not used.

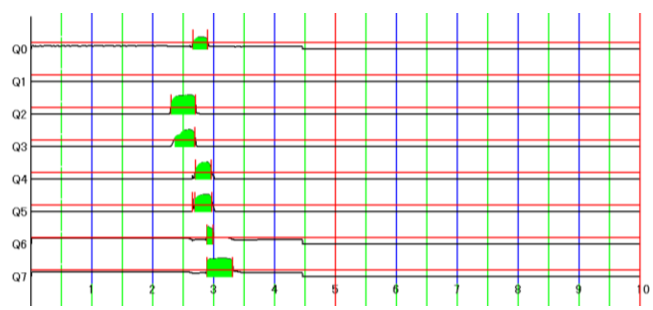

Figure 5. Q sensor output data.

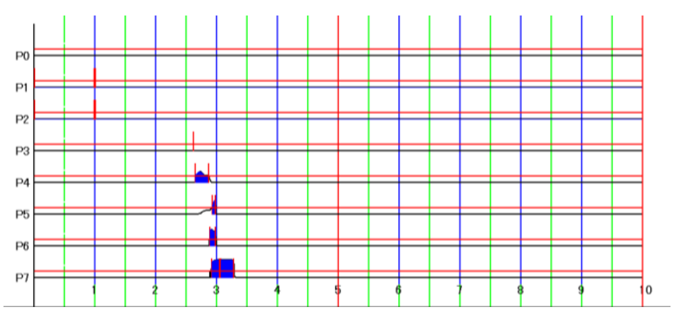

Figure 6. P sensor output data.

Speed was calculated by programming using the LSM. LSM was used so that the relationship between the distance of each sensor corresponding to the time the sensor was stepped on was a linear function (see Figure 7). The slope was obtained as the velocity.

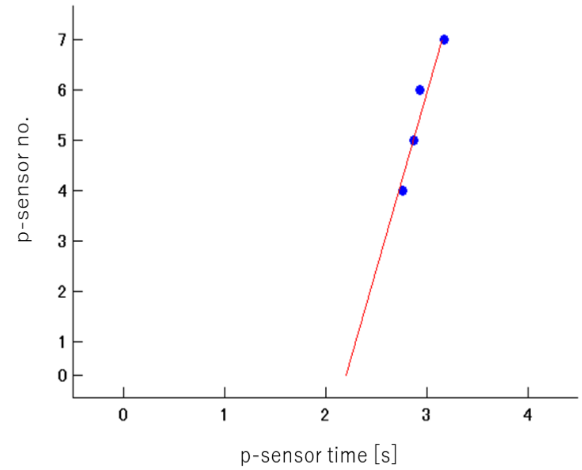

Figure 7. Speed by the least-Squares Method.

Figure 7 shows the time (s) and distance (sensor position), where the inclination of the red line is the speed. The least-squares method was used, assuming a linear function.

Subsequently, a footprint diagram was drawn by examining the raw data from the P and Q sensors, plantar ground contact was determined, and the speed was calculated. When two sensors were stepped on simultaneously at the same time by a single sole, it was assumed to be a single ground contact, and the position and time in the middle of the two sensors were used to determine the speed. It was calculated directly by a manual process (Direct calculations regarding floor mats: DCF1).

The judgment terms in DCF1 were as follows: (1) If there was an output that appeared to be noise that was not understood for a short time, the plantar ground contacts were judged to be grounded when ten consecutive pieces of data were obtained. (2) Data with <2.0% of the maximum value ten times in a row were excluded from sole grounding. (3) When the front and rear sensor data responded simultaneously, the same plantar contact was assumed when >70% of the front sensor data overlapped the rear data. (4) When adjacent P-sensors did not respond consecutively, that is, there was one or more unresponsive P sensors in between, we assumed a different plantar ground contact. Two major differences were noted between LSM and DCF1 for speed using footprint diagrams. First, LSM calculates the speed based on the position and time of each sensor, regardless of whether the two sensors are stepped on simultaneously. The speed by DCF1 is calculated by judging when two sensors are outputting simultaneously, whether they are one footprint or two footprints, that is, the same grounding. Second, it determines whether to use data with small values or responses in the calculation, or to exclude them and treat them as noise. In addition, we compared the TUG test results with sensor array data. An occupational therapist evaluated and validated the videos. On the sensor array, subjects walked straight ahead, whereas on TUG test, subjects walked straight ahead and then U-turn. The speeds on the TUG test were converted and compared with the LSM and DCF1 results from the sensor array data.

2) Walking on a floor mat wearing shoes with sensors

a) Walking measurements

Three subjects walked on a floor mat wearing shoes equipped with pressure and acceleration sensors (see Figure 8).

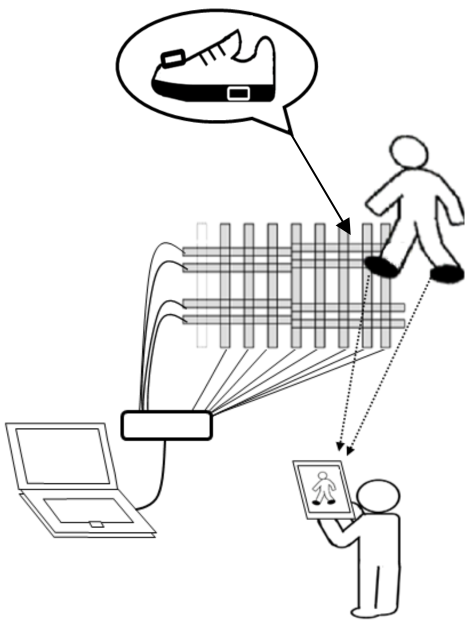

Figure 8. Walking on floor mats with sensor-equipped shoes.

They walked normally without intentional restriction of movement and with the right knee and right ankle joints restricted with supporters. Pressure sensors were placed in the insoles. The acceleration sensors were placed in two locations: one attached to the top of the shoes and one was integrated into the insoles. The video was also recorded while the subjects were walking with the pressure sensor insoles, and the sensor reaction time and video time were synchronized. However, the accelerometer was not synchronized with the video.

b) Analysis

Step times were compared between the floor mats and insoles. Step length and speed were examined between the floor mats, and stride length and speed data were calculated using the analysis application ORPHE TRACK®, which corresponds to the accelerometer ORPHE CORE®. Because the accelerometer was not synchronized with the video, we compared the left and right instead of each step. The judgment terms for plantar grounding were DCF2 in addition to DCF1, the method used for TUG test comparisons. In DCF2, both the P sensor and Q sensor were used. The data with the fastest response among the P and Q sensors were used to determine the time. Although the P sensor does not respond to plantar contact after the P7 sensor, the plantar contact of only the Q sensor, which is not responded to by the P7 sensor, was used in the determination. The determination of the plantar contact position used for calculating the distance was based on only one sensor that responded the earliest using the P sensor.

The judgment terms for DCF2 are as follows: (2) and (3) are the same as those for DCF1. (1) The consecutive data of "Q0Q1 and Q4Q5" on the left side and "Q2Q3 and Q6Q7" on the right side of the floor mat were judged to be the same ground, while those of the left side "Q0Q1, Q4Q5" and the right side "Q2Q3, Q6Q7" were judged to be different grounds. This term was prioritized in determining whether one identical or two grounds were made. (2) When adjacent P-sensors did not respond consecutively, that is, when there was one or more unresponsive P-sensors in between, they were assumed to have different plantar groundings. (3) When two sensor data points (front and rear) responded simultaneously, the same plantar ground contact was assumed when more than 70% of the front sensor data overlapped the rear sensor data. (4) In addition to excluding the calculation when the noise processing was 2% or less of the maximum value, the calculation was also excluded if the same numerical data with a maximum value of 90% or less were continuously repeated five times. However, even if it was 90% or more of the maximum value, the data were considered noise and excluded if 30 consecutive values or 50 intermittently identical values were connected.

Step times were compared between floor mats and insoles by measuring the time taken for one step. An example of insole data is shown in the graph below (see Figure 9). To calculate the distance of the step using the floor mat, the stride length was calculated as the position of the plantar contact when the P sensor first responded. The calculation of step distance using the accelerometer ORPHE CORE® relied on the stride calculated using the analysis application ORPHE TRACK®.

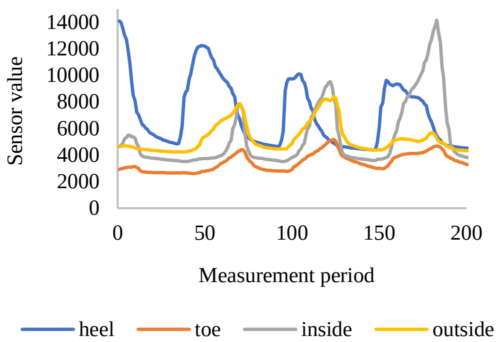

Figure 9. Right insole with normal walking in Case C.

One stride is equal to two steps (see Figure 10). The accelerometer was not synchronized with the video. Hence, a comparison between the data for each step on the floor mat could not be made. Instead of comparing floor mats and acceleration regarding stride length and speed for each step, we made a left–right comparison for step and stride for each floor mat and acceleration. We used the maximum stride length data from the accelerometers for two minutes before and after the measurement. From the floor mats, we only used data that had left and right data, that is, data with more than two steps.

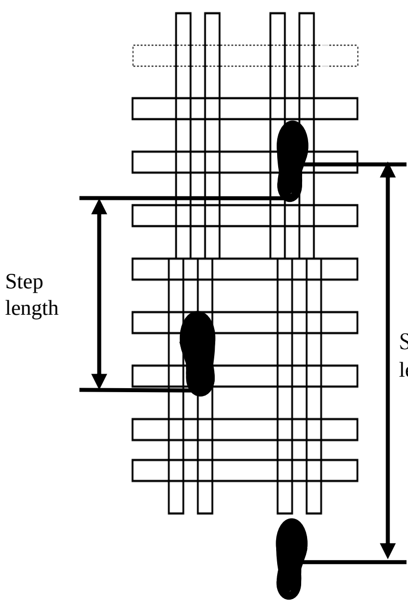

Figure 10. Gait Parameters including step length, and stride length.

The stride length from the accelerometer is the distance from the foot-flat to the foot-flat of one foot. The step length from the floor mat is the distance from one foot to another during a step. The stride and step lengths are not the same (see Figure 10).

III. Results

A. TUG test and Walking on Floor Mat

1) Floor Mat and TUG test Comparison

The speed of the TUG test was compared with that of the subjects walking on a sensor array floor mat. Walking speed on the sensor-placed floor mat was calculated using LSM and DCF1. The mean speeds of Subjects A, B, and C were calculated when they walked comfortably and fast with restricted motion. Figure 11 shows the results for TUG test, LMS, and DCF1. The figure is graphed in ascending order of TUG test speed. In the graph, the first letter corresponds to subjects A, B, and C. The following letter indicates “Rr” for right upper and lower limb restriction, “Lr” for left upper and lower limb restriction, “W” for weight loading, “E” for wearing tinted eye glasses, “c” for comfortable walking, and “f” for fast walking.

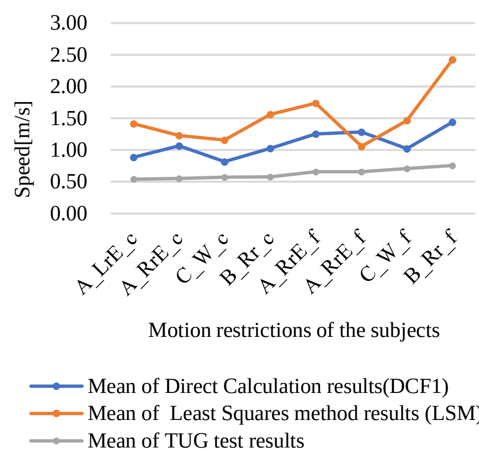

Figure 11. Speed comparison between TUG test and sensor array walking.

The calculation results from the pressure sensor array differed according to the two calculation methods, i.e., LSM by programming and DCF1 by manual calculation using a footprint diagram. In LSM, the calculation result revealed that the speed was slower by three of seven times than the slowest speed in the “left upper and lower limbs and eye limits (A_LrE_c)” TUG test in Case A. In DCF1, the calculation result revealed that only one of the seven times the speed was slower than the slowest speed in the “A_LrE_c” TUG test in Case A. The relationship between TUG test and DCF1, which is a manual calculation using footprint diagrams, is stronger than that between TUG test and LSM using programming. This shows that LSM tends to be faster than DCF1. In the sensor array, walking was measured only straight ahead, whereas in the TUG test, walking was measured both straight ahead and in U-turns. Therefore, the speed of TUG test walking would be slower than that of sensor array walking. The two discrepancies between TUG test and DCF1 were C_ W_c and C_W_f for Subject C. Subject C's walking was assessed on video by an occupational therapist, and a left–right difference was judged. Both C_W_c and C_W_f were observed during plantar grounding of the left foot. The ankle joint ROM in Case C was R20/45 and L-5/50, with a left–right difference.

2) Detection of the Speed of the Left and Right Foot

The results of the speeds calculated by DCF1 for the simulated left and right upper and lower limb movements when restricted are shown in Figures 12 and 13, respectively. Figure 12 shows the right motion restrictions, and Figure 13 shows the left motion restrictions. The X-axis shows comfortable or fast gait with the left or right plantar-grounded foot. The initial letter C in the graph X-axis labels stands for "comfortable" and "F" stands for fast walking. The numbers following the letters C or F denote the number of times performed. The right upper limb lower limb is then indicated by R and the left upper limb lower limb restriction by L. The right and left upper and lower limbs were restricted only in Case A. The color of the bars in the graph is blue when the right plantar is grounded, that is, when the right foot is in the stance phase and the left foot is in the swing phase. Yellow indicates the left plantar-grounded foot, that is, the left foot is in the stance phase and the right foot is in the swing phase. The results when walking faster are indicated by the lines around the bars. Right-side walking, that is, the blue one in the bar graph, tended to be faster than that of the left side, regardless of whether the motions were restricted to the left or right side. The fastest walking was observed when the right foot was grounded, regardless of the left or right side of the upper or lower limb restrictions.

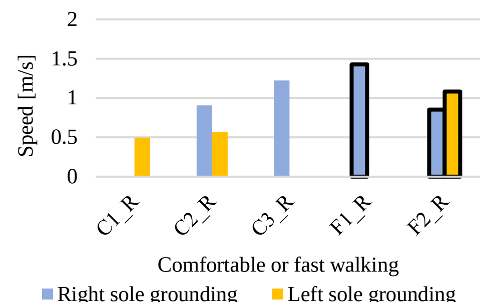

Figure 12. Right upper and lower limb restrictions.

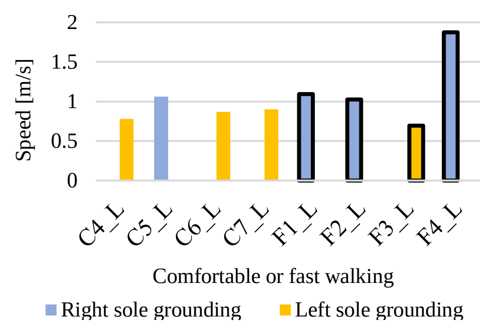

Figure 13. Left upper and lower limb restrictions.

B. *Walking on a Floor mat Wearing Shoes with Sensors*

1) Step Time

The step times were calculated from the floor mats and insoles. The floor mat data were calculated in two ways: using the same method DCF1 as TUG test and a new method DCF2 with some modifications. The walking performance of three subjects was conducted 13 times, with the number of steps taken on a floor mat ranging from 1 to 3 per performance, and the total number of steps was 30.

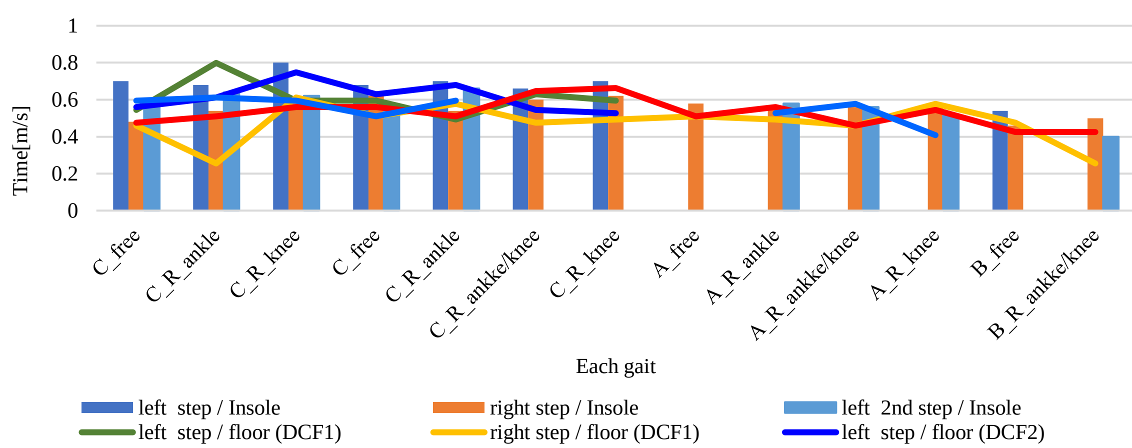

Figure 14. Step time detected from floor mats and pressure sensor insoles.

Of the four parts of the insole (toe, heel, inside, and outside), the heel with a clear sensor response to ground contact was used. We measured the time from when the heel was on to when the other heel was on. The results for 30 data points are shown in the graph (see Figure 14).

The bar graph indicates the step time determined from the insole, and the line graph indicates the step time determined from the floor mat. In the graph, three bar graphs in one walking sequence indicate that three steps were performed on the floor mat. The two-bar graphs represent the two steps and a single step taken on the floor mat in one bar. Left foot grounding after the right foot was labeled as the left second step. The left foot is blue, light blue, and green in the bar graph, and navy and blue in the line graph. The right foot is orange on the insole, and red and yellow on the floor mat. The letters after the numbers indicate that "R_ankle" represents the restriction of the right ankle and "R_knee" represents the restriction of the right knee.

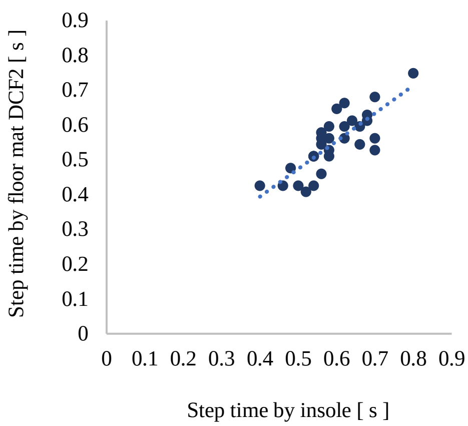

Figure 15. Step time by floor mat DCF2 and insole.

We observed that DCF2 had a higher correlation with the insole data than DCF1. Therefore, we performed a correlation analysis between 30 pairs of data from the insole and the DCF2. The Pearson correlation coefficient was 0.80 (see Figure 15).

2) Left–right Comparison of Step and Stride

The step and stride lengths of the left and right sides were compared. The number of steps taken per walk ranged from 1 to 3, allowing for four trials in which the left and right sides could be compared for two or more steps. The total number of data points was eight. The graph shows the stride length calculated from the floor mat and the maximum stride length in 2 min calculated from the accelerometer (see Figures 16 and 17).

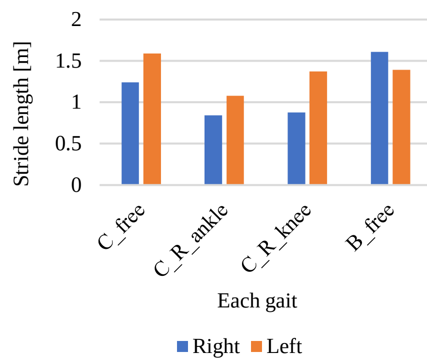

Figure 16. Maximum stride length from the accelerometer.

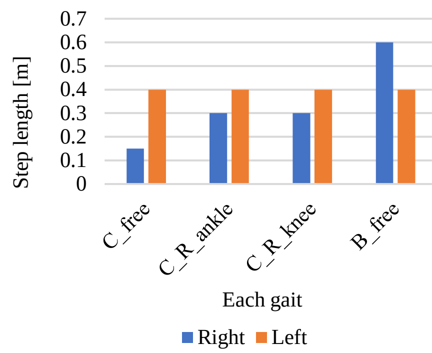

Figure 17. Step length from the floor mat.

The graph shows a similar trend in the left－right comparison of stride length calculated by the accelerometer and step length calculated by the floor mat. As for C_free, the left－right balance of the floor mats and accelerometers is very different. Upon checking the video, it was confirmed that the left sole makes plantar contact slightly farther away from the P2 sensor and closer to P3. The subject stepped on the P3 sensor with the toes and not on the P2 sensor. Then, only the right heel stepped on P4. This pattern of slightly stepping on or not stepping on the sensor was repeated twice.

3) Left–right comparison of speed

Using the same method as for the aforementioned steps and strides, the speed was calculated four times over two steps and eight times for the left and right sides combined. Speeds were calculated from the times and distances obtained from the previous items 2) and 3), and compared to the left and right. The speed calculation using the floor mat used the time of the foot that was not in contact with the ground. For example, the time from right foot contact to left foot contact was calculated as the speed during the left foot swing.

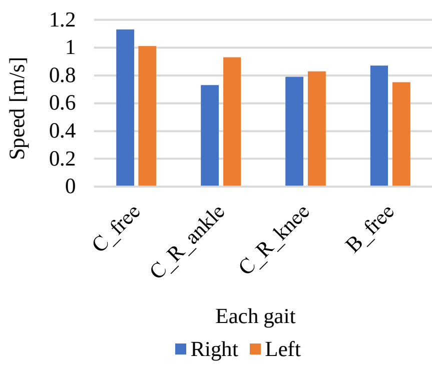

Figure 18. Speed from the accelerometer.

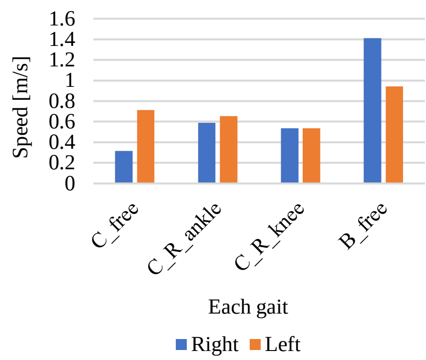

Figure 19. Speed from the floor mat.

The relationship between the speed of the floor mats and acceleration could not be considered as high (see Figures 18 and 19).

IV. Discussion

This floor mat is shorter than conventional gait assessments such as the TUG test. However, because the equipment can be placed at home at all times, considering its size, anything larger than this is not considered practical. The equipment is based on the premise that the detection accuracy will improve as the number of data points increases with daily repetition. Conventional gait assessments are based on a single measurement; therefore, the use of this floor mat differs from conventional assessment methods.

Even with this approximately 120 cm equipment, a high correlation was observed between the insole and the floor mat regarding step time. The correlation was higher in DCF2 than in DCF1 because of the P sensor and also because the Q sensor was included in included in the calculation. It is important to determine whether the left and right soles are in contact and to increase the accuracy of determining the time of sole contact with the parallel Q sensor while walking. Although the Q sensor parallel to the walking gait is considered useful for measuring steps, video observation revealed plantar ground contact that did not step on the parallel sensor on one side. There were some walks on which one of the longitudinal sensors was not stepped on owing to the narrow stride width. To further improve the accuracy of the mat, it may be necessary to slightly narrow the distance between the longitudinal sensors. Regarding the measuring equipment, it is necessary to thoroughly examine it, including the distance between the sensors, in the future, as it may change slightly in noise and sensor position because of its movement to the survey facility and its possible slight changes from one implementation to another.

Regarding speed, there seemed to be a relationship between the speed of the TUG tests, but no strong relationship was found in the left-right comparison with the insoles. This may be because the accelerometer was not synchronized with the video and could not investigate each step individually. It could also be attributed to the floor mat's low accuracy in step length determination. In the gait where there was a large difference in the left–right balance of step and stride length from the floor mat and accelerometer, the left sole made plantar contact slightly farther away from the P2 sensor but closer to P3. The P3 sensor was stepped on with the toes, but the P2 sensor was not stepped on. Subsequently, only the right heel stepped on P4. This pattern of slightly stepping on or not stepping on the sensor was repeated twice. A solution to this problem would be to slightly narrow the distance between the P sensors. Although it depends on the body size of the subject and gait distance, narrowing the vertical sensor installed in parallel with the gait and the horizontal sensor at right angles by approximately 2 cm is thought to improve the accuracy.

This study was experimentally conducted using a floor mat sensor intended for repeated use in activities of daily living. Although the data sample size is small and generalization is not possible, the high correlation with accurate insole data suggests a high potential for usefulness. The ability to measure gait daily at home would be useful not only for the early detection of disease and disability, but also for the treatment of those with fluctuating physical conditions such as rheumatism, those whose activity capacity changes under the influence of medications such as the on-off phenomenon of Parkinson's disease, and those with rhythm disorders. Reports have shown that walking speed assessment at home differs from that in a laboratory setting [5]. Walking during dual tasking is slower than walking alone. In daily life, walking is often used as a means of transportation to perform activities. Walking during dual tasking is slower than walking alone. Attention must also be paid to environmental factors, such as flooring and objects, and sudden stimuli, such as someone approaching. Attention may also be low in a low-awareness state. Occupational and physical therapists routinely assess walking conditions but do not always use measuring devices or quantify them. They observe and assess their interactions with the patients, and health conditions are determined based on the patients' gait. If walking conditions could be measured naturally in daily life, it would be possible to assess walking ability without a therapist. This also leads to objective data showing the therapist's tacit knowledge and experience [2].

Measuring walking ability in daily life at home can help provide information that cannot be obtained from laboratory or hospital measurements.

V. Conclusion and Future work

Regarding the floor mat used, the usefulness of step time was suggested, although challenges were associated with step length. The floor mat has the potential to predict health changes. The ability to measure walking ability during daily activities at home is thought to be useful in providing life support, self-care, and diagnostic assistance to older people and the disabled, as well as in understanding what is unknown from measurements taken in the hospital. Although the amount of data is small, there seems to be a strong correlation with high-accuracy smart insoles, suggesting that they may be useful. In the future, we plan to increase the amount of data and conduct further investigations to generalize our findings. Studies have already been conducted on synchronizing acceleration and pressure sensors attached to shoes.

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