Wearable 6MWT Measuring System for Clinical Application

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Abstract: The six-minute walk test (6MWT) is an effective clinical tool for evaluating cardiopulmonary function and exercise endurance. This study proposes an automatic measuring system for the 6MWT using wearable accelerometers, aiming to solve the problems of the traditional 6MWT, which relies on manually recording a single parameter of the six-minute walk distance (6MWD). The proposed system will increase the comprehensiveness and clinical applicability of the 6MWT evaluation by automating the testing process and systematizing data management. Since the wearable accelerometer can be worn on the head, waist, and ankle, we investigated the gait parameters that could be extracted at each location and compared the difficulty of their extraction. The results indicate that the data obtained from the ankle can be used to extract more parameters to describe gait characteristics in more detail. As a clinical application, we proposed a step length-cadence distribution map for the 6MWT using critical thresholds of the 6MWD, which is the most commonly used to assess cardiovascular disease, chronic respiratory disease, and sarcopenia.

Key-Words: *Six-minute walk test, six-minute walk distance, wearable accelerometers, step length-cadence*

1. Introduction

The World Health Organization's report in 2020 shows that cardiopulmonary diseases have become the leading cause of death, and disability rates are increasing among the elderly [1]. With the aging of the population, improving the quality of life of the elderly and extending their expected healthy life has become an important social concern [2]. Walking, as an easy-to-perform and low-cost form of exercise, helps maintain muscle strength, enhance cardiopulmonary function, improve mental health, and promote social interaction. It has been widely used in nursing care and rehabilitation medicine around the world [3].

The six-minute walk test (6MWT) is a commonly used standardized assessment method for evaluating exercise endurance and cardiopulmonary function by measuring the maximum distance when a patient walks in 6 minutes [4]. The 6MWT is safe, widely applicable, and does not require complex equipment. Participants only need to walk along a fixed track for 6 minutes, and medical staff record the six-minute walking distance (6MWD) using a tape measure. Compared with other walking tests, such as 5-meter or 10-meter tests, the 6MWT provides a more comprehensive reflection of their physical health and ability to live independently, because the 6MWT requires participants to walk as fast as possible for longer periods of time. It is extremely valuable in clinical applications.

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Since gait changes can effectively reveal an individual's health status and disease progression in clinical practice, accurately acquiring of gait characteristics in the 6MWT is essential. Currently, 6MWD is a common indicator for doctors to evaluate the cardiopulmonary function of patients, but how 6MWD reflects overall health is still largely unknown. For example, gait parameters such as walking speed, cadence, step length, and stability are also important in assessing the health status of older adults [5]. In addition, the traditional 6MWT relies on manual observation and must be conducted in a specific place, which limits their applicability, and lacks systematic data management and long-term analytical capabilities. Therefore, development of a 6MWT automated data acquisition system for long-term health monitoring has become a key research topic.

To compensate for the shortcomings of the conventional method, we developed a system to automatically collect and manage 6MWT gait data obtained from the wearable accelerometers. The system employs two different wireless communication methods to accommodate a variety of measurement scenarios. Since the accelerometers can be worn on the head, waist, and ankles, the influence of acceleration data at each location on the extraction of feature parameters was investigated. Finally, a method to automatically calculate gait parameters such as stride length, step length, gait speed, and 6MWD was presented, and its usefulness was verified by a clinical application of visualizing the differences in walking distance using gait distribution map.

2. Methodology

2.1 Overview

Inertial accelerometers have been the most used sensors in 6MWT-related studies. Drover et al. used accelerometers to monitor gait data in older adults performing 6MWT and developed a method for fall classification [6]. To assess the physical activity level of the elderly, Karavirta et al. similarly used accelerometers to collect 6MWT data [7]. These studies suggest that accelerometers have great potential for gait monitoring and health assessment. Therefore, this study will establish a data collection and management system suitable for 6MWT with accelerometers.

2.2 Wearable accelerometers

The wearable sensor device includes a TWELITE accelerometer sensor unit (Mono Wireless Inc., Japan) and a 3V coin battery. The device, with dimensions of 20×20×10mm, weight of 6.5g, and sampling rate of 50Hz, has good wearability to effectively support walking monitoring needs.

In general, the head movement represents the balance of the upper body, the waist location reflects the movement of the body's center of gravity, and the ankle contains more detailed leg movement information. In this study, the devices were worn at the three places, the head, waist, and ankle, as shown in Figure 1.

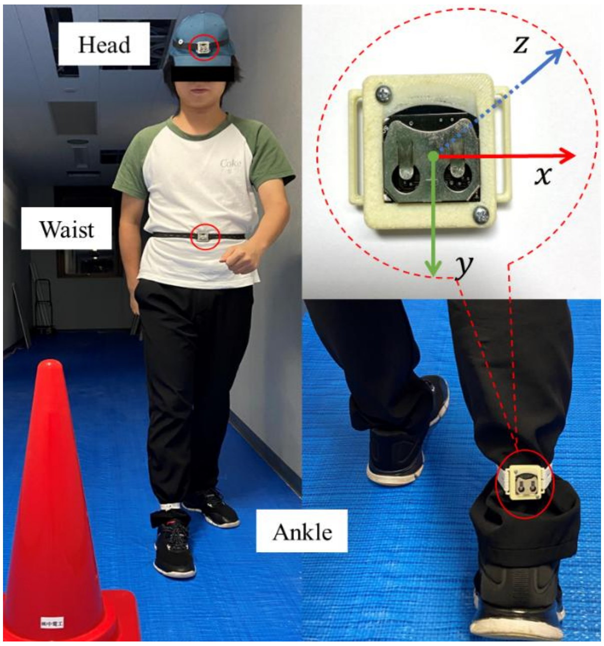

Fig.1 Schematic diagram of sensors worn on the head, waist, and ankle using elastic bands (Installation method at the ankle Location, Downward: positive y-axis; Forward: positive z-axis; Rightward: positive x-axis).

2.3 Device design for different scenarios

We developed two data transfer methods for different application scenarios. The first method involves converting TWELITE wireless signals to Wi-Fi and transmitting sensor data to a web server. The second method transfers data directly to a smartphone.

Figure 2 depicts an application scenario at medical institutions, rehabilitation centers, and nursing homes, where the data is transferred via Wi-Fi to a web server for continuous data transfer, enabling multi-person gait tests and compatibility with other clinical equipment. Gait data collected by the accelerometer is wirelessly transmitted to a signal repeater, which converts it to a Wi-Fi signal via serial communication and uploads it to the data processing center.

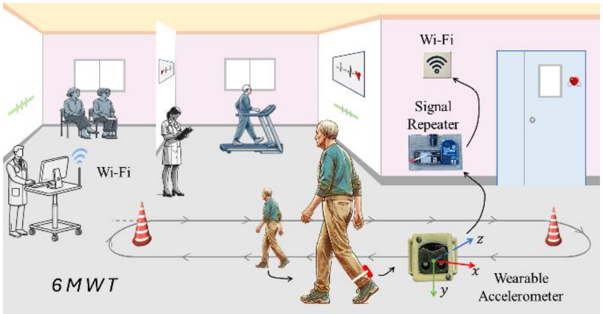

Fig.2 A data collection method using Wi-Fi.

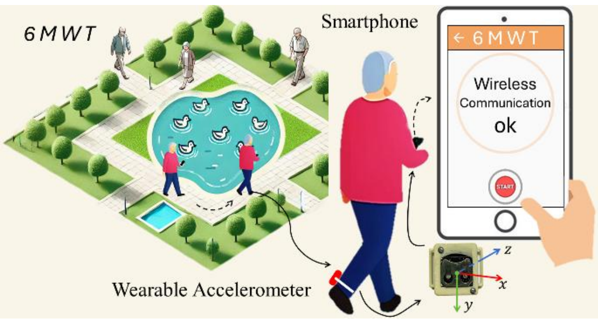

Fig.3 A data collection method using smartphone.

Figure 3 depicts an outdoor scenario, where the device is connected wirelessly to a smartphone via a small signal receiver attached to the USB port, facilitating quick data collection of gait data and generation of test results. The two transfer methods are easy to operate, with a signal reception success rate exceeding 95%, ensuring data reliability and stability for subsequent analysis.

2.4 Experiment

Since motion patterns vary across body parts, the acceleration signal differs significantly based on sensor placement. In clinical practice, it is important where the sensor is attached. Therefore, we collect gait acceleration data at each part of the body, investigate the influence of motion patterns' extraction and the effects on gait characteristics.

In the experiment, three wearable accelerometers were attached to the head, waist, and ankle, respectively (Figure 1). Participants walked for 6 minutes on a standardized track, as shown in Figure 2, with a straight-line distance of 20m between two conical barrels, following the 6MWT guidelines [4].

2.5 Gait acceleration data

Figure 4 shows a portion of the triaxial acceleration data collected from the head, waist, and ankle sensors during the 6MWT. Clinically, medical personnel usually only record the distance of straight-line walking and ignore the U-turn walking based on the walking track in Figure 2. The x-axis signal from the ankle location shows a sudden increase in acceleration during the U-turn parts, so we can easily mark the straight-line and U-turn parts with A and B using a low-pass filter and peak detection, as shown in Figure 4.

Accurate identification of the gait cycle is the basis for extracting spatiotemporal parameters such as step length, step cadence, and walking speed. The cycle of gait can be divided based on the ground reaction force at the moment when the foot touches the ground detected by the ankle accelerometer using local peak points. The markers ①, ② and ③ in Figure 4 represent the start and end points of two walking cycles.

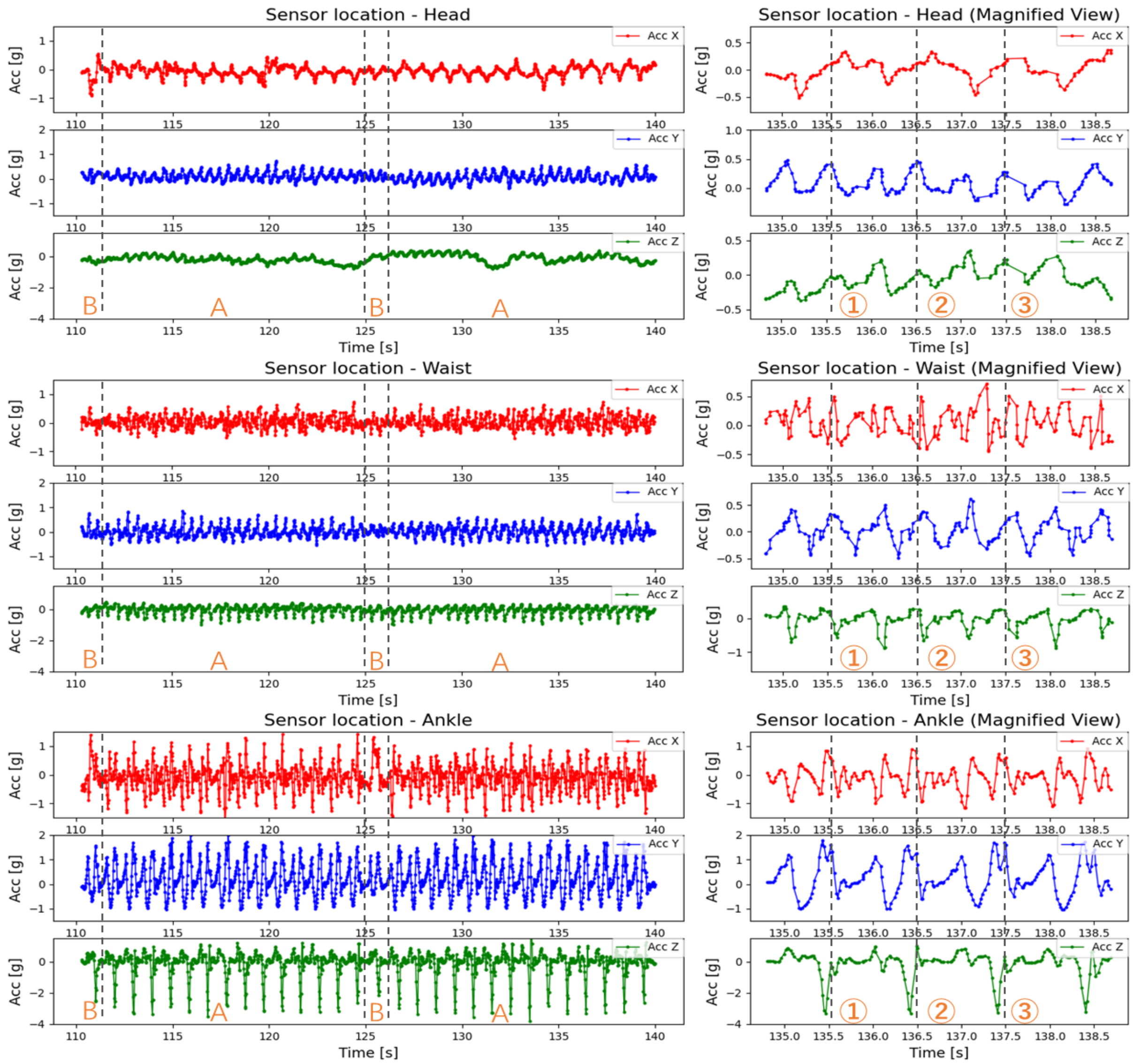

Fig.4 A portion of the acceleration data collected from sensors worn on the head, waist, and ankle during the 6MWT.

3. Results and Discussion

3.1 Feasibility Analysis

A simple way to determine the gait period is to apply an FFT (Fast Fourier Transform) to the signal [8]. Since the x-axis signal is less periodic, Figure 5 shows the results of applying the FFT to the y-axis and z-axis signals from the head, waist, and ankle.

On the other hand, the time of each step can be easily extracted from ankle accelerometer signals by detecting their peaks at the moment when the foot contacts the ground. The obtained average step time is 2.13^{-1} [s/step], which is exactly same as that obtained by applying FFT to the accelerometer signals at the waist and ankle.

Therefore, FFT analysis shows that the head mainly reflects the gait cycle, whereas the waist and ankle positions contain more frequency components, with the ankle providing the most gait information.

Furthermore, the head sensor is susceptible to head swings, and the waist sensor can mainly represent the moving features of the center of gravity. While extracting them requires more advanced signal processing techniques, it is possible to extract features for each phase of the gait cycle from the foot sensor.

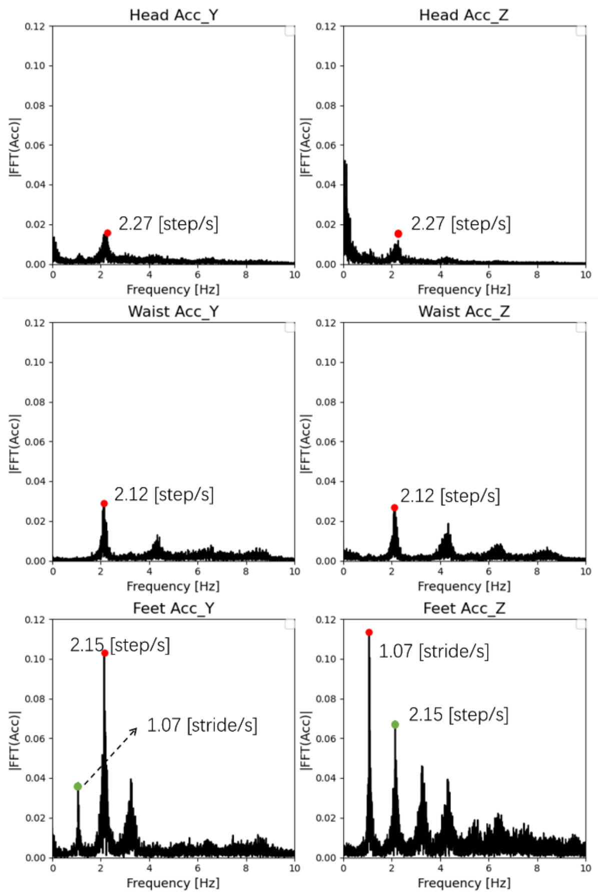

Fig.5 FFT analysis results of the y-axis and z-axis from the head, waist, and ankle signals, with step time corresponding to 2.27^{-1}, 2.12^{-1}, and 2.15^{-1} [s/step], respectively, for the main frequency components.

Table 1 presents the difficulty of extracting gait parameters in gait kinematics, phase, and kinetics, where ○ indicates easier extraction, △ indicates difficult extraction, and – indicates unclear signal. Regarding kinematic parameters, the step count and cadence can be easily extracted regardless of where the sensor is attached. However, we found that the head and waist signals could not effectively differentiate between straight-line and U-turn walking in Figure 4, leading to unclear segmentation of the 20m straight-line walking parts, further affecting the calculation of the walking distance, step length (calculated 20m divided by step count), and walking speed (calculated the product of step length and cadence). For the phase parameters, the signal from the head or the waist were affected mainly by the movements of head or the center of gravity of body, it makes difficult to clearly identify the timing of the double-leg support, single-leg support, and swing phases. Finally, for kinetic parameters, acceleration values can represent the states of acceleration, deceleration, and braking in walking. These can only be clearly obtained from the ankle signals, but not be possible from the head and waist signals.

Table 1: Difficulty in Extracting Gait Parameters.

	Kinematic Parameters					Phase Parameters			Kinetic Parameters	
	Step Count	Step Length	Step Cadence	Walking Distance	Walking Speed	Gait Cycle	Stance Phase	Swing Phase	Y-axis Acceleration	Z-axis Acceleration
Head	○	△	○	△	△	△	–	–	–	–
Waist	○	△	○	△	△	△	–	–	–	–
Ankle	○	○	○	○	○	○	○	○	○	○

Note, ○: Easy; △: Difficult; –: Unclearly obvious.

3.2 Gait characteristics

With the above analysis, we focused on analyzing the ankle signals to extract gait features. Figure 6 shows the kinematic characteristics and gait phases of the y-axis and z-axis data at the ankle, where the marks ①, ②, and ③ correspond to the three states in Figure 4. The figure accurately marks the length and cadence of each step and shows the states corresponding to the different movements. Step length is the distance between successive placements of opposite feet, while step cadence represents the inverse of the placement time. Also, the stance phase is the time when the foot begins to contact the ground and support the body weight. The swing phase is the time when the foot leaves the ground and moves forward.

Figure 6 shows that the ankle gait signal can clearly and intuitively obtain the gait parameters listed in Table 1. These parameters compensate for the shortcomings of conventional assessments that rely solely on gait distance, providing not only richer gait data, but also important data support for clinical diagnosis and rehabilitation assessment.

For example, step length and cadence can be used to assess changes in lower limb muscle function, while the duration and ratio of the support phase and swing phase reflect the balance and stability of gait [9, 10].

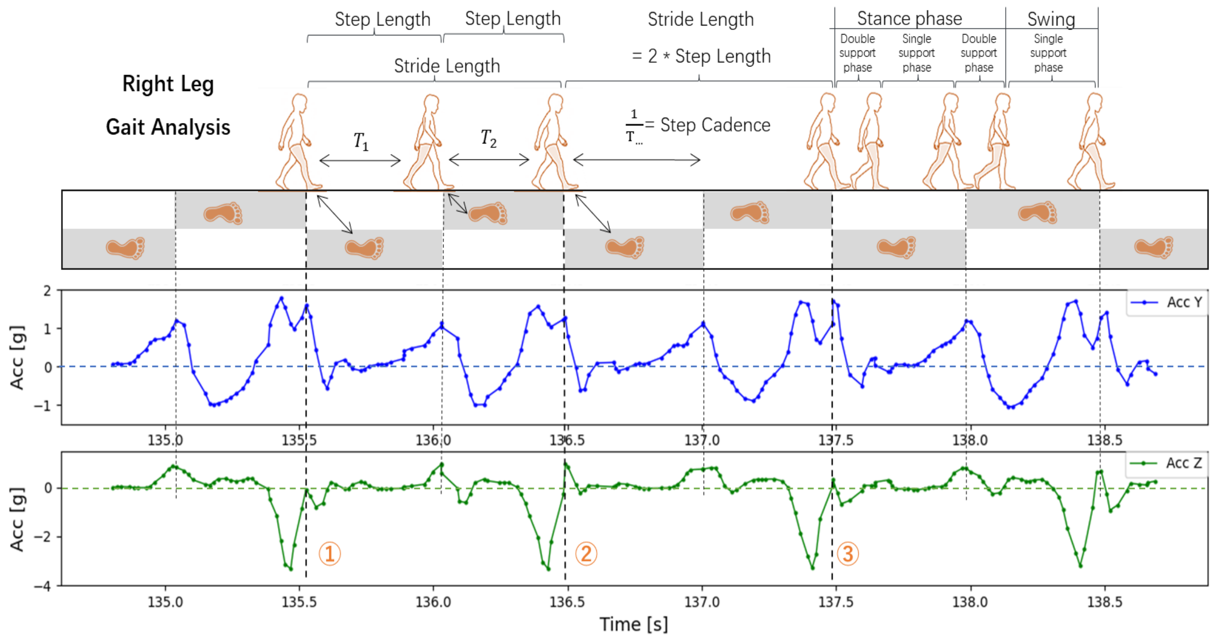

Fig.6 Kinematic characteristics and gait phases of the y-axis and z-axis in ankle signals.

3.3 Clinical applications

The 6MWD is the most commonly used gait parameter in the clinical 6MWT. Related studies demonstrated a strong relationship between 6MWD and a variety of age-related diseases, including cardiovascular disease, chronic respiratory disease, sarcopenia, and cognitive dysfunction. The total distances at 300m and 400m are usually regarded as key thresholds, where a 6MWD above 400m tends to indicate good cardiorespiratory function and Physical activity ability outside the home, while below 300m may be in higher risk of disease and mortality for older adults [9].

In this study, besides extracting multiple gait parameters through 6MWT, we further explore the difference between the calculated 6MWD and the distances recorded by medical personnel observations. Moreover, substituting the thresholds of 300m and 400m using basic gait spatiotemporal parameters of step length and cadence, thereby demonstrating the gainful role of gait analysis in assessing the health status of older adults.

We collected 6MWT gait data from 60 elderly participants (46 males and 14 females, age 72±5years, weight 63±12kg, height 163±8cm) with normal walking ability. For data processing, firstly, the step length was calculated by recognizing the number of steps in the 20m straight-line walking parts. Subsequently, the step cadence was calculated by FFT analysis and the walking speed was calculated from the product of the step length and cadence. Finally, an estimation of 6MWD is obtained by the cumulative distance of all complete straight-line walking segments.

Figure 7 shows the distribution of spatiotemporal parameters of gait in 10 elderly, where the horizontal axis is the step cadence and the vertical axis is the step length, and each point represents the average value of each straight-line walking part in the 6MWT. Since the product of the step cadence and the step length equals walking speed, we added two speed thresholds in the distribution map, where the green dashed line represents 1.33m/s and the red dashed line represents 1.00m/s. Two thresholds were derived from a linear regression analysis of 6MWD with speed (r = 0.98, y = 286.77·x + 18.90), corresponding to walking distances of 400m and 300m, respectively.

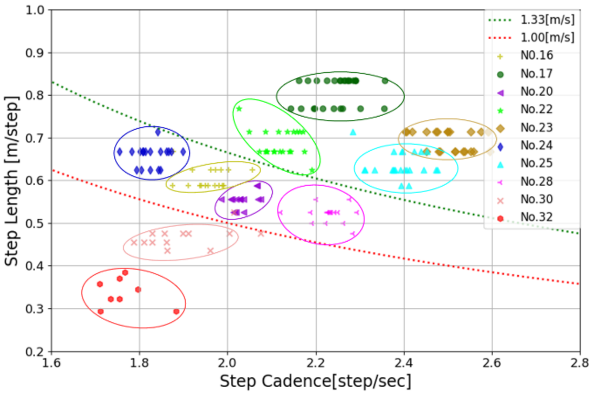

Fig.7 The gait distribution map of 10 elderly people.

This distribution map not only visualizes the assessment of walking distance on the health status of the elderly, but also shows the distribution of different gaits at the same distance, and the range of gait fluctuations during walking. Compared with the results of the clinical diagnosis of frailty according to the revised Japanese version of Cardiovascular Health Study (J-CHS) criteria [9], plots lower than the red dashed line were mainly in a frail state, while plots higher than the green dashed line were almost in a normal state. Furthermore, the clinical applications also validated our previous observation that a single walking distance may have limitations in assessing physical condition and cannot fully reflect the health status of the elderly. For example, even when walking the same distance, a larger step cadence or stride might indicate a completely different muscle condition, and the differences in gait fluctuations might conceal the secret of whether the elderly person will fall or not.

4. Conclusion

This study developed an automated analysis system for 6MWT using wearable accelerometers that can effectively capture the gait characteristics of older adults and be used for health assessment. The difficulty of extracting gait parameters was analyzed on signals from three positions: head, waist, and ankle. We also presented gait parameters that were very consistent with clinical observations. As for clinical applications, the gait distribution map with two speed thresholds was proposed for providing richer information about physical health and a new perspective for the health management of the elderly.

In future research, we will focus on extending the functionality for early prediction of disease risk in the elderly, further contributing to personalized medicine for the elderly.

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