Doctoral Dissertation

博士論文

Gait Pattern Analysis and Lower Limb Muscle Weakness Evaluation Using Wearable 6MWT System

「ウェアラブル６分間歩行テストシステムを用いた歩行パターン解析と下肢筋虚弱評価」

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Contents

Ethical Review Approval Certificate

The study was approved by the Institutional Review Board under Ethics Review No. H2021-031.

List of terms and abbreviations

Terms / Abbreviations	Description
5mWT	5-Meter Walk Test
6MWD	6-Minute Walking Distance
6MWEE	6-Minute Walk Energy Expenditure
6MWT	6-Minute Walking Test
AFA	Acceleration-Based Filtering Angle Algorithm
ASA	Anterior Shank Angle
ASMI	Appendicular Skeletal Muscle Mass Index
AUC	Area Under the Curve
AWGS	Asian Working Group for Sarcopenia
BIA	Bioelectrical Impedance Analysis
BMR	Basal Metabolic Rate
CHS	Cardiovascular Health Study
CI	Confidence Interval
COPD	Chronic Obstructive Pulmonary Disease
CTAA	Coordinate Transformation Angle Algorithm
DXA	Dual-Energy X-Ray Absorptiometry
EX	Exhaustion of the J-CHS
FFT	Fast Fourier Transform
FPR	False Positive Rate
GV	Gait Velocity
HBE	Harris-Benedict Equation
HS	Handgrip Strength
IIR	Infinite Impulse Response
J-CHS	Japanese Version of the Cardiovascular Health Study
MET	Metabolic Equivalent of Task
MSA	Multi-Sensor Fusion Angle Algorithm
PA	Physical Activity of the J-CHS
PSA	Posterior Shank Angle
QOL	Quality of Life
ROC	Receiver Operating Characteristic
SAA	Synthesized Acceleration Algorithm
SC	Step Cadence
SL	Step Length
SP	Walking Speed of the J-CHS
SPPB	Short Physical Performance Battery
SS-5	Five Times Sit to Stand Test
TPR	True Positive Rate
TUG	Timed Up and Go Test
WHO	World Health Organization
WL	Weight Loss of the J-CHS
WMS	Walking Muscle Strength
WS	Walking Speed

Abstract

Improving the quality of life (QOL) and extending healthy life expectancy among older adults have become important issues in today's aging society. Age-related decline in muscle function (sarcopenia) and musculoskeletal disorders can lead to reduced ability to perform daily activities and an increased risk of falls, which significantly impair QOL. To maintain the health of the elderly, early detection and appropriate intervention of these problems are essential.

Clinically, handgrip strength (HS) and walking speed (WS) are commonly used indicators of physical function and are included in both the Japanese version of the Cardiovascular Health Study (J-CHS) and the Asian Working Group for Sarcopenia (AWGS) criteria to assess frailty and sarcopenia. Walking is not merely a means of mobility but a fundamental and vital activity essential for maintaining musculoskeletal and cardiovascular health. Studies reported that walking plays a crucial role in preventing muscle function decline and musculoskeletal disorders, making walking ability a key factor in knowing the health status of older people.

However, the J-CHS criteria consist of five items (n=5): two physical indicators (HS and WS) and three questionnaire-based items (unintentional weight loss, self-reported exhaustion, and reduced physical activity) to assess frail (n≧3), pre-frail (n=1~2), or non-frail (n=0) individuals. Since these criteria heavily rely on questionnaire responses, they represent a semi-objective evaluation method and may not accurately identify physical frailty due to muscle decline. Furthermore, they lack numerical indicators to quantify the severity of muscle weakness. Additionally, the walking speed cutoff value of 1m/s (5m walk test) is used, and the assessments of exhaustion and physical activity that depend on personal subjective perception reveal a lack of objective methods.

On the other hand, the 6-minute walking test (6MWT) is widely used clinically to assess exercise capacity in patients with chronic respiratory and cardiac diseases. The 6-minute walking distance (6MWD) is an important indicator for evaluating a patient's exercise endurance and its impact on daily life. Studies reported that a 6MWD below 400m is associated with limitations in daily walking. Patients with chronic respiratory or cardiac diseases are prone to becoming frail, especially those with chronic obstructive pulmonary disease (COPD), which is known to have a high prevalence of frailty. This study focuses on the effectiveness of the 6MWT for assessing exercise endurance, and aims to objectively and early detect physical frailty by measuring and analyzing 6MWT data. The goal is to support early intervention, prevent the progression of frailty, and promote the extension of healthy life expectancy.

Moreover, there is a pressing problem with the lack of objective numerical indicators to quantify the severity of the condition in both the J-CHS criteria for assessment of frailty and the AWGS criteria for evaluation of sarcopenia. Without such indicators, it is difficult to accurately assess the effectiveness of interventions or monitor disease progression. Assuming that a new indicator can be developed to quantitatively assess walking-related muscle function decline and improvement after intervention using data from the 6MWT, it could help optimize personalized medical care and rehabilitation programs.

Additionally, current methods of measuring stride length are limited to calculating averages over fixed distances, making it difficult to capture individual gait changes or visualize detailed walking patterns. The ability to accurately estimate 6MWD even in environments where straight-line distance measurement is not possible, and to provide more detailed gait analysis data, could contribute to the development and evaluation of personalized walking guidance programs for the elderly by healthcare professionals.

This study focuses on evaluating exercise endurance in older adults and aims to develop a wearable device that enables easy implementation of the 6MWT. The device uses an accelerometer to collect walking data and calculates detailed gait parameters such as step length, cadence, walking speed, and distance. Comparing the diagnostic results with the J-CHS criteria, this study aims to establish a method for assessing physical frailty due to lower limb muscle function decline. Furthermore, a new index called the Walking Muscle Strength (WMS) index is introduced and compared with the J-CHS criteria-based assessment of frailty and the AWGS criteria-based assessment of sarcopenia to verify its validity and utility in visualising disease severity and intervention outcomes. Additionally, an algorithm is developed to calculate stride length, walking speed, and the angle range of lower leg motion at each stride based on walking data and a method is proposed to visualise the results of gait analysis without relying on a fixed straight line course. The results of this study are expected to contribute to the early detection of frailty and sarcopenia, and to support appropriate interventions to improve QOL and extend healthy life expectancy in the elderly.

This paper consists of six chapters.

Chapter 1 introduces the background and purpose of this study.

In Chapter 2, to solve the limitation of traditional 6MWT manual recording and the problem of assessing exercise capacity using mainly the 6MWD and average walking speed, a wearable device was developed. This device automatically collects data in various environmental conditions. To more effectively obtain detailed gait data, such as step length and step cadence, the optimal location of the wearable sensors was determined, and algorithms were developed to accurately calculate the gait parameters.

In Chapter 3, to address the issue that the subjective metrics included in the J-CHS criteria for assessing frailty prevent an objective assessment of physical frailty, various gait-related indicators during the 6MWT, such as walking speed, stride length, and cadence, were extracted. Based on the correlation analysis between these indicators and the items of the J-CHS criteria, a new frailty assessment method using 6MWT gait data was proposed. The effectiveness of the proposed method was verified through comparison with diagnostic results in clinical evaluation according to the J-CHS criteria.

In Chapter 4, to address the lack of indicators for quantitatively assessing the walking-related muscle weakness and the effectiveness of interventions in the elderly, the relationship between 6MWT data and 6-minute walk energy expenditure (6MWEE) was investigated. Based on this analysis, a new WMS index was proposed, and its effectiveness was examined by comparisons with diagnostic results based on the J-CHS and AWGS criteria. Additionally, the usefulness of the WMS index was demonstrated from the perspective of quantitatively visualizing disease progression and improvements achieved through rehabilitation.

In Chapter 5, to accurately calculate lower leg swing angles and stride distances from 6MWT data, with the aim of providing objective gait analysis data to help physical and occupational therapists promote safe and efficient walking, an algorithm was developed. This approach addresses the limitations of traditional stride distance measurements, which calculate average stride length by dividing a known distance by the stride counts, but this method is problematic when the walking distance is unknown. By applying the proposed algorithm, the 6MWD can be accurately estimated even in environments where distance measurement is difficult, and detailed gait characteristics can be visualised by capturing individual gait changes.

Chapter 6 summarizes the conclusions and future perspectives of this study.

要 旨

高齢化が進む現代において、高齢者の QOL(生活の質)向上と健康寿命の延伸は重要な課題となっている。加齢に伴う筋機能低下(サルコペニア)や筋骨格系障害は、日常生活動作能力の低下や転倒リスクの増加を招き、QOL を著しく損なう要因となる。これらの問題を早期に発見し、適切な介入を行うことが、高齢者の健康維持には不可欠である。

フレイルの診断基準である J-CHS 基準やサルコペニアの AWGS 基準では、共通の身体機能指標として握力(HS)と歩行速度(WS)が用いられている。歩行は単なる移動手段に留まらず、筋骨格系および循環器系の健康維持に不可欠な基本的かつ重要な活動である。歩行が筋機能低下や筋骨格系障害の予防に最も重要であるという報告があり、歩行能力の評価は高齢者の健康状態を把握する上で重要な鍵となる。

しかし、J-CHS 基準は、2 つの身体機能指標(HS、WS)と 3 つの質問項目(意図しない体重減少、自己申告による疲労、身体活動の低下)の合計 5 項目で構成され、3 点以上をフレイル、1 点以上をプレフレイル、0 点をノンフレイルと評価する。この基準は調査票に大きく依存した半客観的な評価方法であるため、筋機能低下による身体的フレイルを正確に特定できない場合があり、また、筋力低下の程度を定量化した指標が提示されていない。さらに、歩行速度の閾値(5m 歩行テストで 1m/s)の採用や、身体的な疲労感や身体活動状態の評価は個人の主観に依存し、客観的な推定方法が不足している。

一方、臨床現場では、慢性呼吸器疾患や心疾患患者の運動能力評価に 6 分間歩行テスト(6MWT)が広く用いられている。6 分間歩行距離(6MWD)は、患者の運動耐容能や日常生活への影響を判断する重要な指標である。先行研究では、6MWD が 400m 以下の場合は、日常生活における歩行能力に制限があることが報告されている。慢性呼吸器疾患や心疾患を患う患者は、フレイルを発症しやすい傾向にあり、特に慢性閉塞性肺疾患(COPD)患者では、フレイルの合併率が高いことが知られている。本研究では、6MWT が運動耐容能評価に有能である点に着目し、歩行データを計測・分析することで、身体的フレイルを客観的かつ早期的に発見し、早期介入による重症化予防と健康寿命の延伸に貢献することを目指す。

また、現在の J-CHS 基準によるフレイル診断や AWGS 基準によるサルコペニア診断では、病態の程度を数値で示す客観的な指標が不足しており、介入効果の評価や病態進行の正確なモニタリングが困難であるという喫緊の課題を抱えている。6MWT から歩行筋機能低下や、その後の介入による改善効果を定量的に評価するための新しい指標があれば、個別化された医療介入やリハビリテーションの最適化に貢献することが期待される。

現在の歩幅測定方法は、一定距離での平均値算出に留まり、個々の歩容変化の把握や詳細な歩行状態の可視化が困難という課題がある。直線距離測定が困難な環境でも 6MWD を正確に推定し、より詳細な歩容分析データを提供できれば、医療専門職が高齢者などへの個別最適化された歩行指導プログラムの立案と評価に寄与することが期待される。

本研究では、高齢者の運動耐容能評価に着眼し、6MWT を簡便に実施できるウェアラブルデバイスを開発する。このデバイスは加速度センサで歩行データを計測し、そのデータから歩幅、歩調、歩速、距離などの歩容に関する詳細なパラメータを正確に算出する。J-CHS 基準の

診断結果と比較・検討することで、下肢筋機能低下に起因する身体フレイルの評価方法を確立する。さらに、歩行筋力強度(WMS)指数を新たに導入し、J-CHS 基準によるフレイル診断結果ならびに AWGS 基準によるサルコペニア診断の結果と比較検討し、病態評価または介入効果の可視化における有効性と有用性を検証する。さらに歩行データから各歩の歩幅や速度、下腿部の角度可動域を算出するアルゴリズムを開発し、既定のコースに依存しない歩容の分析結果を可視化する方法を提案する。本研究で得られた成果は、フレイルやサルコペニアの早期発見と適切な介入が可能になることで、高齢者の QOL 向上と健康寿命の延伸に貢献することが期待される。

本論文は、6 章から構成される。

第 1 章では、本研究の背景と目的について述べる。

第 2 章では、従来の 6MWT における手動記録の限界と、運動能力指標が主に 6MWD および 6 分間平均速度に限定される課題に対処するため、ウェアラブルデバイスを開発した。このデバイスは、データの自動収集と多様な環境下での測定を可能にする。さらに、歩幅や歩調といった詳細な歩行データをより効果的に取得するため、ウェアラブルセンサの最適な取り付け位置と、歩行パラメータを正確に算出するアルゴリズムを確立した。

第 3 章では、フレイル評価基準である J-CHS 基準に含まれる主観的な指標が身体的虚弱性の客観的評価を妨げるという課題に対し、6MWT 中に得られる多様な歩行データ指標(例：歩行速度の変動、歩幅、歩調など)を抽出した。これらの指標と J-CHS 基準の各項目との関連性を詳細に分析した結果に基づき、6MWT の歩行データのみを用いた新しいフレイル判定方法を提案した。提案手法の有効性は、臨床検査における J-CHS 基準による診断結果との比較検討により検証された。

第 4 章では、高齢者の歩行筋機能低下や、介入による改善効果を定量的に評価する指標が不足しているという課題に対し、6MWT データと 6 分間歩行エネルギー消費量(6MWEE)の関係性を調査した。この分析に基づき、新しい指標である歩行筋力強度(WMS)指数を提案し、J-CHS 基準および AWGS 基準による診断結果との比較検討を通じて、WMS 指数の有効性を検証した。また、病態進行評価およびリハビリテーション等による改善効果の定量的可視化の観点からその有用性を示した。

第 5 章では、理学療法士や作業療法士が安全で効率的な歩行を促進するための客観的な歩容分析データを提供することを目的に、6MWT データに基づき下腿部の振れ角度と各歩の距離を精度よく算出するアルゴリズムを開発した。これにより、従来の一歩の距離測定方法(一定距離を歩かせ、その距離を歩数で割る)における課題、すなわち直線距離が未知の場合に各歩の距離算出が困難であるという問題が解決される。本アルゴリズムを適用することで、直線距離測定が困難な環境においても 6MWD を正確に推定し、個々の歩容変化を捉えることで詳細な歩行状態を可視化する方法について述べる。

第 6 章では、論文全体のまとめと今後の展望について述べる。

Chapter 1 Introduction

1.1 Research background

Currently, the world is experiencing rapid population aging [1, 2]. Figure 1.1 shows the trend in the proportion of people over 65 years of age in major countries (1950-2070) published by the Ministry of Internal Affairs and Communications of Japan in 2024, it is projected that the proportion of people over 65 years of age in the world will reach about 10% by 2025, while in Japan it will rise to about 30%, which is the highest in the world [3]. The rapid aging of the population has caused a series of age-related health problems, and the incidence of chronic diseases in the elderly population is increasing rapidly, especially cardiovascular diseases, chronic respiratory diseases, frailty, joint diseases, and sarcopenia [4, 5]. This situation not only increases the burden on the healthcare system but also significantly increases the cost of care and nursing in society [4, 5].

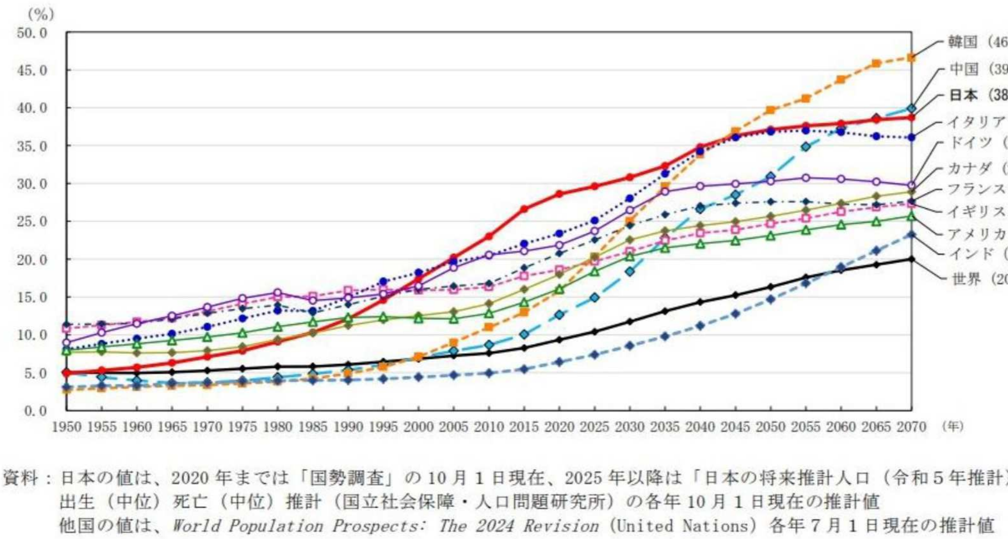
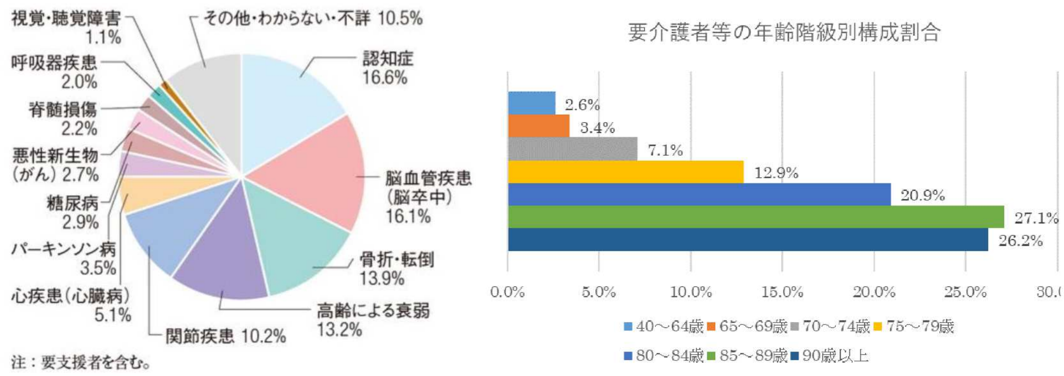


Figure 1.1 Trends in the proportion of the world's population aged 65 and over (1950-2070)

Since the concept of healthy life expectancy was introduced by the World Health Organization (WHO) in 2000, there has been a growing interest in how to live longer and improve quality of life [6]. Healthy life expectancy differs from the traditional indicator of average life expectancy in that it refers to the number of years that a person is able to live independently and is free from serious health problems, such as reduced mobility or the need for long-term care. In other words, healthy life expectancy focuses not only on how long one lives but also on maintaining good health and physical functioning during the aging process. In contrast, unhealthy life expectancy refers to the period of time during which an individual lives with an illness, infirmity, or disability, and requires assistance from others. As the population ages, unhealthy life expectancy is directly related to the burden on healthcare systems, the need for care resources, and the quality of life of older people [7].

To further explore the reasons why elderly people need care, we refer to data from the Comprehensive Survey of Living Conditions published by the Ministry of Health, Labour and Welfare of Japan [8]. Figures 1.2(a) and 1.2(b) show the main reasons that older adults need care and the age distribution of caregivers, respectively. Figure 1.2(a) shows that as many as 37.3% of the conditions are strongly associated with a decline in muscle function, including fractures and falls (13.9%), age-related frailty (13.2%), and joint disorders (10.2%). This suggests that over a third of care needs can be attributed to muscular and body movement system diseases. In addition, Figure 1.2(b) indicates that the need for care begins to increase after the age of 65, reflecting the increasing cumulative effect of muscle deterioration and loss of physical function with age. Therefore, early intervention and resistance training to prevent and delay muscle deterioration are important to prolong a healthy lifespan and improve the quality of life of older adults [9, 10].



(a) **(b)**

Figure 1.2(a) shows the percentage of the main reasons why older people need care, and (b) shows the age distribution of those who need care.

Muscle is one of the most basic and important tissues in the human body and play a vital role in maintaining life and health [11]. Its main functions include contraction and relaxation under voluntary control, which helps maintain posture, balance, and bone stability. Additionally, muscle plays an important role in glucose regulation, fat metabolism, and energy expenditure [12]. However, with age and physiological changes, there is a gradual decline in muscle mass and strength, leading to limitations in basic physical activities such as walking, climbing stairs, and lifting in older adults [13]. These limitations can negatively impact daily life and may lead to age-related diseases such as sarcopenia, weakness, falls, and even cognitive decline [14]. Therefore, muscle function is regarded as a key indicator for exploring the aging process and evaluating individual health [15].

Decline in muscle function in older adults is one of the most common and important physiological changes during aging. It is usually characterized by slow gait, weakness, and fatigue, which gradually affects the ability to live independently. This functional decline is mainly due to two factors: reduction in muscle mass and decrease in muscle strength [16]. Muscle mass generally refers to the total amount of skeletal muscle in the body, which is often expressed in terms of muscle volume or weight.

Dual-energy X-ray absorptiometry (DXA) and bioelectrical impedance analysis (BIA) are widely recognized as the gold standard for evaluating muscle mass, especially appendicular skeletal muscle mass index (ASMI) [16]. Although DXA and BIA provides high accuracy, its high cost limits its use in routine, large-scale screening. Muscle strength refers to the maximum force produced by a muscle during contraction. It depends not only on the amount of muscle mass but also on factors such as neural transmission efficiency and muscle activation coordination [17]. Muscle strength is commonly assessed in two ways: 1) direct measurement of upper limb strength using a handgrip dynamometer and 2) indirect assessment of lower limb strength, most commonly using walking speed to estimate lower limb strength levels. [16] Thus, Clinically, handgrip strength (HS) and walking speed (WS) are widely used as indicators of upper and lower limb muscle strength and have been included in both the Japanese Revised Cardiovascular Health Study (J-CHS) and the Asian Working Group for Sarcopenia (AWGS) criteria to assess frailty and sarcopenia in the elderly [16, 18, 19].

Frailty is a clinical syndrome characterized by physical, psychological, and social vulnerability. Researchers have proposed various diagnostic criteria for frailty, including the CHS [20], J-CHS [18, 19], FRAIL scale [21], frailty index [22], and Kihon checklist [23]. Most of these criteria evaluate the severity of frailty through patient- or physician-reported questionnaires and subjective assessments. Currently, the J-CHS criteria have been widely recognized as the gold standard for clinical diagnosis. The J-CHS includes two physical items (HS and WS) and three questionnaire items (unintentional weight loss, self-reported exhaustion, and reduced physical activity), totaling five items to assess frailty, pre-frailty, or non-frail [18,19]. Sarcopenia is a clinical condition characterized by age-related loss of muscle mass accompanied by reduced muscle strength and/or decreased physical performance. The AWGS evaluates sarcopenia using the ASMI, HS, and WS [16]. Currently, the diagnosis of frailty is mainly based on the five items of the J-CHS criteria: three or more items are considered frail, one or two items are considered pre-frail, and none are considered non-frail. According to the AWGS criteria, when muscle mass plus HS or WS are not met it is sarcopenia, and when all are not met it is severe sarcopenia. Given that the thresholds for HS (Men<28 kg, Women<18 kg) and WS (1.0 m/s) are the same in current assessment methods, there is a large overlap between cases of frailty and sarcopenia. Both conditions directly contribute to a decline in physical function, making a person more susceptible to injury and potentially increasing the risk of disease and disability in older people.

Although frailty and sarcopenia are important for evaluating muscle function and predicting adverse health outcomes, they are not exactly the same. Some individuals with frailty may not have sarcopenia, and those with sarcopenia may only be in a prefrail state. Many researchers have observed both conditions together and found that more than half of frailty cases are caused by physical factors such as sarcopenia, while the rest are caused by psychological or social factors [24, 25]. Studies suggest that early and targeted intervention may help older adults who are already frail gradually return to a pre-frail state or even recover to a healthy status [26]. It is important to note that frailty is not only related to physical function decline but also includes psychological and social aspects. Psychological and social frailty often manifests as weight loss, depression, fatigue, and reduced social activity. In such cases, where physical function is still relatively preserved, timely interventions such as nutritional support, psychological counseling, and encouragement to participate in social activities can often lead to good improvement. However, this does not imply that all frail individuals can recover through simple social support. Intervention is generally more difficult, especially for those whose frailty is caused by physical factors such as sarcopenia.

Currently, the J-CHS and AWGS criterias are considered the gold standards for the assessment of frailty and sarcopenia. However, both methods have limitations in practical applications. First, the J-CHS method heavily relies on questionnaire-based surveys, especially when assessing physical fatigue and activity, which are entirely dependent on individuals' self-reports. This reliance can affect the accuracy of the assessment results. Second, as a semi-objective assessment method, the J-CHS model cannot accurately identify physical frailty caused by muscle function decline. Moreover, the J-CHS method requires older adults to visit medical institutions for diagnosis, which not only fails to meet the continuous care needs of the elderly but also increases the burden on informal caregivers. More importantly, both the J-CHS and AWGS criterias lack objective indicators to quantify the severity of the condition, making it difficult to evaluate the effectiveness of interventions and monitor disease progression, thereby impacting the development of effective intervention strategies. It is important to note that the assessment of muscle function should not focus solely on the diagnosis of frailty or sarcopenia. Once these conditions are diagnosed, the individual is often already at a relatively low level of physical function, possibly with an irreversible loss of muscle mass and strength. Therefore, it is truly meaningful to describe and quantify muscle conditions that represent different "preclinical stages" before the onset of frailty or sarcopenia, providing strong support for personalized medical interventions and rehabilitation outcome assessments.

To recognize physical frailty and assess muscular function more accurately, it is necessary to focus on physical activity [27, 28]. Some studies, such as Toosizadeh et al.'s upper limb elbow flexion exercise [29], Bortone et al.'s gait analysis [30], and Greene et al.'s timed up and go (TUG) test [31], have demonstrated certain feasibility in frailty assessment, yet they do not fully elucidate the relationship between the main causes leading to physical frailty and the decline in muscle function and motor ability.

Moderate physical activity positively influences muscle contraction strength and immune cell function [32]. Andersen et al. conducted upper limb resistance training using dumbbells and resistance bands and found that muscle activation levels, as shown by electromyography, increased significantly during training [33]. Farinatti et al. recommended a high-intensity, low-volume training program, such as brisk walking and squats, three times per week, which can significantly improve muscle strength in older adults [34]. In addition, the study by Cadore et al. indicated that aerobic exercises such as brisk walking can not only improve muscle mass and strength in the elderly but also help reduce frailty in very old populations, such as those aged 90 years and above [35]. Current physical activity interventions are often approached separately from both the upper and lower limb perspectives. However, in daily life, lower-limb function has a more direct impact on the independence of older adults, especially in activities such as walking, climbing stairs, and other outdoor movements. Compared to high-intensity or complex exercises, walking, which represents lower-limb function, is a low-intensity, sustainable, and low-risk form of physical activity. This may be the only suitable option for most older adults. Walking is the easiest form of physical activity and is available to everyone with no specific disease [36]. Studies reported that walking plays a crucial role in preventing muscle function decline and musculoskeletal disorders, and walking ability is a key factor in determining the health status of older people [37]. Thus, we believe that monitoring walking activity can provide a better understanding of muscle health and early intervention for the onset of frailty and sarcopenia.

Walking is a representative form of aerobic exercise that can improve lower-limb muscle contraction and cardiorespiratory endurance. A stable gait is a basic requirement for performing various activities and living independently [38]. Walking speed is the most important parameter for assessing lower limb muscle function. It is widely used to identify health risks and prevent chronic diseases, and is considered the sixth vital sign [39]. According to Hayashida et al., walking speed is closely related to knee extension muscle strength and muscle mass measured using BIA [40]. Lim et al. showed through biomechanical analysis that walking speed has a significant effect on muscle fiber length and ground reaction force generated by muscles [41]. Also, a decrease in gait speed reflects a decline in upper limb HS, and Watsford et al. further pointed out that it is also related to respiratory muscle function [42].

Walking speed is usually measured as the ratio of distance to time, and it can also be expressed as the product of step length (SL) and step cadence (SC) [41, 43]. However, there is still no clear consensus regarding the relationship between SL, SC, and muscle function in older adults. Although muscle mass is not equivalent to muscle strength, Riviati et al. pointed out that muscle mass is crucial for the formation of muscle strength [44]. The amount of muscle mass is mainly determined by the combination of the number of muscle fibers and the cross-sectional area of each muscle fiber. Muscle fibers can be broadly classified into fast-twitch and slow-twitch fibers. Fast-twitch fibers have a larger cross-sectional area, contract quickly, and generate high force, and they are mainly responsible for high-intensity and short-duration movements, such as jumping or lifting heavy objects. In contrast, slow-twitch fibers contract more slowly and are more fatigue-resistant. They are mainly involved in low-intensity and long-duration activities such as maintaining posture or walking for extended periods. A report by runners found that SL was significantly and positively correlated with the slow-speed group, but not significantly correlated with the fast-speed group [45]. We speculate that SL may reflect muscle extensibility and may be related to the state of slow-twitch fibers that represent persistent and low-intensity exercise. In addition, our investigations showed that athletes' changes in SC increased significantly and exceeded the surpassing changes in SL during uniform and sprint running [45]. This suggests that the SC may represent the state of fast-twitch fibers that generate instantaneous force in muscles. Therefore, we speculated that using SL and SC instead of gait speed may provide a more detailed assessment of sarcopenia and physical frailty caused by lower-limb muscle weakness.

In recent years, various standardized walking test methods have been widely used in clinical practice and rehabilitation. These tests are mainly classified into three types: the 5-meter walk test (5mWT), which focuses on speed; the Timed Up and Go test (TUG), which focuses on time; and the 6-minute walk test (6MWT), which focuses on distance. The 5mWT is mainly used to assess walking speed. Walking speed below 0.8 m/s, it usually indicates limited mobility and has been used as an early predictor of healthy life expectancy [46]. If the speed drops further below 0.6 m/s, it is strongly associated with increased mortality and hospitalization risk in older adults [47]. The TUG test involves a sequence of movements, including standing up, walking 3 m, turning around, and sitting down. When the time to complete the test exceeds 13.5 seconds, a higher risk of falling is indicated [48]. The 6MWT is a classic test for assessing functional aerobic endurance and is widely used in patients with chronic obstructive pulmonary disease (COPD), heart failure, and geriatric syndromes. It evaluates the cardiopulmonary endurance and disease severity [49]. Studies have shown that a walking distance of > 400 m is usually associated with good physical activity levels and lower cardiovascular disease risk [50]. However, a distance less than 300 m is often linked to higher mortality and fall risk [51]. Patients with chronic respiratory or cardiac diseases are prone to becoming frail, especially those with COPD, which is known to have a high prevalence of frailty [52].

Compared with other short-duration tests, the 6MWT has the advantage of a longer testing period and includes a cognitive task (participants are required to walk as far as possible within the time limit), making it better at reflecting a person's ability to sustain activities in daily life. This allows for a more accurate evaluation of the overall physical function. Additionally, physiological parameters such as heart rate, oxygen saturation, and changes in walking speed during the test can be measured to assess cardiopulmonary responses under near-maximal effort conditions [53]. As a result, the 6MWT has gained increasing attention in both clinical and research settings in recent years, especially in geriatric medicine and chronic disease management.

Currently, the 6-minute walking distance (6MWD) is the only indicator used in the 6MWT in clinical practice. Although the 6MWD can reflect, to some extent, an individual's health status and disease progression, there is still significant uncertainty regarding how well it represents overall health. This is because apart from walking distance, other gait parameters such as gait velocity (GV), SL, SC, and joint angles are also important for assessing the health condition of older adults. Therefore, relying only on the 6MWD cannot fully reveal the complex physiological processes reflected in gait changes, and it is necessary to combine multiple gait parameters for a comprehensive analysis. In studies investigating the relationship between the 6MWT and diseases related to declining muscle function, such as frailty and sarcopenia, most researchers reached a similar conclusion: as age increased, muscle mass and strength gradually decreased, and the corresponding 6MWD tended to decrease. Although this conclusion is widely accepted and statistically supported, many of these studies have focused only on outcome-level analysis and lack a detailed investigation into the underlying muscle condition. Consequently, it remains difficult to understand the specific level of muscle strength and individual differences reflected by the 6MWD.

As of now, the survey found that only a few existing studies have used the 6MWT as an intervention tool for resistance training to guide and analyze walking in older adults. This limits their potential clinical applications. The traditional 6MWT relies on manual observation and must be conducted in designated spatial facilities to easily calculate the 6MWD, which poses a challenge to medical institutions with limited space. Additionally, current methods of measuring stride length are limited to calculating averages over fixed distances [54], making it difficult to capture individual gait changes. If it becomes possible to accurately estimate the 6MWD even in environments where straight-line distance measurement is not feasible, and to provide more detailed gait analysis data, it would help healthcare professionals in developing and evaluating personalized walking guidance programs for older adults. In Japan, the 6MWT is implemented in hospitals or specialized rehabilitation centers and is covered by health insurance; however, the shortage of trained professionals remains a challenge, particularly in some facilities where elderly caregivers support other elderly individuals.

1.2 Research purposes

This study aimed to develop a wearable measurement system for the 6MWT and propose a method for evaluating lower limb muscle weakness. We extracted various gait patterns and compared them with the diagnostic results of the J-CHS criteria to assess and visualize physical frailty caused by reduced muscle function. Moreover, we proposed a new concept, the Walking Muscle Strength (WMS) index, and compared it with the diagnosis results of frailty and sarcopenia to demonstrate its effectiveness and usefulness in visualising disease severity and rehabilitation outcomes. Furthermore, we developed an algorithm based on 6MWT acceleration data to provide medical practitioners with more detailed gait analysis data, thus helping them to make effective walking advice based on the distribution of gait parameters in the elderly. To achieve these objectives, this study was organized into the following four questions:

(1) To address the limitations of the traditional 6MWT, which relies on manual measurement and uses 6MWD or average walking speed as the only gait parameter to assess exercise capacity.

A 6MWT automated analysis system using wearable accelerometers was developed to continuously monitor and extract gait patterns to assess lower-limb muscle function.

(2) To solve the problem of the J-CHS method in accurately identifying physical frailty caused by reduced muscle function.

A gait distribution map was proposed based on the relationship between slow-twitch and fast-twitch muscle fibers and two independent gait parameters, SL and SC, as a substitute for walking speed. The map was used to assess and visualize the physical frailty related to muscle function decline and was further compared with the J-CHS method to validate the contribution of our approach to frailty assessment.

(3) To solve the lack of quantitative metrics in the J-CHS and AWGS criterias for assessing the degree of disease, rehabilitative effects of interventions, and walking-related muscle weakness.

The concept of the WMS scale is presented as a multivariate function of SL, SC, and six-minute walk energy expenditure (6MWEE) for the assessment of walking muscle strength. The correlations of the WMS with 6MWD, speed, and handgrip strength were then explored, and finally compared with frailty and sarcopenia assessed by J-CHS and AWGS criterias, for the quantitative aspects of disease progression and rehabilitation improvement effects, to illustrate the validity of the WMS score.

(4) To address the problem of further calculating the leg swing angle and stride distance from the 6MWT acceleration data, thus providing detailed gait analysis data to help physicians make suggestions based on objective data to promote a safe and efficient gait in the elderly.

In the 6MWT, the maximum posterior shank angle (PSA), maximum anterior shank angle (ASA), and walking distance for each stride were estimated. These gait patterns were then compared with the normal movable angle range of dorsiflexion in the ankle joint, as well as with the distances and angles of normal walking and large-stride walking, to provide a reference for the physician making individual and numerical for walking advice.

1.3 Article structure

This paper is divided into six chapters, and the content of each chapter is arranged as follows.

Chapter 1 describes the background and purpose of this study.

Chapter 2 describes a 6MWT system using a wearable accelerometer, which is proposed and designed to support two modes of data transmission, Wi-Fi and smartphones, to target different application scenarios. It also illustrates that a clearer and more comprehensive gait pattern can be obtained at the ankle by comparing the ease of gait parameter extraction using wearable accelerometers worn on the head, waist, and ankle.

Chapter 3 describes the correlation between the gait parameters obtained from the 6MWT system and frailty, pre-frailty, and non-frailty, as assessed by the J-CHS, and identifies two key thresholds to classify four gait distributions representing different muscle states of the lower limbs. Two thresholds were determined through Receiver Operating Characteristic (ROC) analysis of SL and SC with the five metrics of the J-CHS criterion. Four gait distributions describe the muscle status through fast and slow muscles in muscle fibers and are compared with the J-CHS method to show that the region with the weakest muscle status is almost frail, and the region with normal muscle status is mostly non-frail, to validate the practicality of our method in the assessment of physical frailty.

Chapter 4 presents the concept of WMS score based on the 6MWT, which is defined as a multivariate function of SL, SC, and 6MWEE. Next, the WMS score was normalized using a sigmoid function and divided into four levels representing lower limb muscle strength. A comparison of the results with the diagnosis of frailty and sarcopenia based on the J-CHS criteria and the AWGS criteria showed that most of the patients with frailty were located in the weakest level, while all the patients with sarcopenia were located in the weakest and second weakest levels, with those diagnosed with severe sarcopenia falling into the weakest levels, demonstrating the effectiveness of our method for quantifying muscle strength.

Chapter 5 introduces an algorithm for estimating the maximum PSA, ASA, and walking distance. The algorithm combines the walking acceleration cycle change with gait kinematic analysis, first predicts the time-series position in which the maximum PSA and ASA are in each cycle, then uses the principle of zero-speed updating in the gait cycle, and finally estimates the PSA, ASA, and walking distance for each stride. Distribution histograms of different gait patterns were plotted, and PSA was analyzed in comparison with the normal movable angle range of dorsiflexion in the ankle joint surveyed reference, ASA, and walking distances compared with the angle and distances corresponding to the reported normal and large stride walking, thus providing a visual basis for doctors to making walking guidance for the elderly.

Chapter 6 describes the conclusions and future prospects of this study.

References

[1] Yonei Y. Global Trends in Anti-Aging Medicine[M]//Anti-Aging Medicine: Basics and Clinical Practice. Singapore: Springer Nature Singapore, 2025: 9-11.22

[2] Xi J Y, Liang B H, Zhang W J, et al. Effects of population aging on quality of life and disease burden: a population-based study[J]. Global Health Research and Policy, 2025, 10(1): 2.

[3] Statistics on the elderly in Japan (Published by the Ministry of Internal Affairs and Communications): https://note.com/cyo99/n/nd10507dcf6c5 (accessed on 4 April 2025).

[4] Guo J, Huang X, Dou L, et al. Aging and aging-related diseases: from molecular mechanisms to interventions and treatments[J]. Signal transduction and targeted therapy, 2022, 7(1): 391.

[5] Jaul E, Barron J. Age-related diseases and clinical and public health implications for the 85 years old and over population[J]. Frontiers in public health, 2017, 5: 335.

[6] Life expectancy and healthy life expectancy: https://www.who.int/data/gho/data/themes/mortamort-and-global-health-estimates/ghe-life-expectancy-and-healthy-life-expectancy (accessed on8 April 2025).

[7] Choi M, Sempungu J K, Lee E H, et al. Living longer but in poor health: healthcare system responses to ageing populations in industrialised countries based on the Findings from the Global Burden of Disease Study 2019[J]. BMC Public Health, 2024, 24(1): 576.

[8] Overview of the 2022 National Living Basics Survey: https://www.mhlw.go.jp/toukei/saikin/hw/k-tyosa /k-tyosa22/dl/14.pdf (accessed on 6 April 2025).

[9] Fragala M S, Cadore E L, Dorgo S, et al. Resistance training for older adults: position statement from the national strength and conditioning association[J]. The Journal of Strength & Conditioning Research, 2019, 33(8).

[10] McPhee J S, French D P, Jackson D, et al. Physical activity in older age: perspectives for healthy ageing and frailty[J]. Biogerontology, 2016, 17: 567-580.

[11] Frontera W R, Ochala J. Skeletal muscle: a brief review of structure and function[J]. Calcified tissue international, 2015, 96: 183-195.

[12] Merz K E, Thurmond D C. Role of skeletal muscle in insulin resistance and glucose uptake[J]. Comprehensive Physiology, 2011, 10(3): 785-809.

[13] Nilwik R, Snijders T, Leenders M, et al. The decline in skeletal muscle mass with aging is mainly attributed to a reduction in type II muscle fiber size[J]. Experimental gerontology, 2013, 48(5): 492-498.

[14] Tieland M, Trouwborst I, Clark B C. Skeletal muscle performance and ageing[J]. Journal of cachexia, sarcopenia and muscle, 2018, 9(1): 3-19.

[15] Agostini D, Gervasi M, Ferrini F, et al. An integrated approach to skeletal muscle health in aging[J]. Nutrients, 2023, 15(8): 1802.

[16] Chen L K, Woo J, Assantachai P, et al. Asian Working Group for Sarcopenia: 2019 consensus update on sarcopenia diagnosis and treatment[J]. Journal of the American Medical Directors Association, 2020, 21(3): 300-307.

[17] Reggiani C, Schiaffino S. Muscle hypertrophy and muscle strength: dependent or independent variables? A provocative review[J]. European journal of translational myology, 2020, 30(3): 9311.

[18] Satake S, Arai H. The revised Japanese version of the Cardiovascular Health Study criteria (revised J-CHS criteria)[J]. Geriatrics & gerontology international, 2020, 20(10).

[19] Satake S, Arai H. Frailty: Definition, diagnosis, epidemiology[J]. Geriatrics & gerontology international, 2020, 20.

[20] Fried L P, Tangen C M, Walston J, et al. Frailty in older adults: evidence for a phenotype[J]. The journals of gerontology series a: biological sciences and medical sciences, 2001, 56(3): M146-M157.

[21] Morley JE, Malmstrom TK, Miller DK. A simple frailty questionnaire (FRAIL) predicts outcomes in middle aged African Americans. J Nutr Health Aging. 2012;16(7):601–608.

[22] Searle SD, Mitnitski A, Gahbauer EA, Gill TM, Rockwood K. A standard procedure for creating a frailty index. BMC Geriatr. 2008 Sep 30;8:24.

[23] Satake S, Senda K, Hong YJ, Miura H, Endo H, Sakurai T, Kondo I, Toba K. Validity of the Kihon Checklist for assessing frailty status. Geriatr Gerontol Int. 2016 Jun;16(6):709-15.

[24] Morley J E. Frailty and sarcopenia in elderly[J]. Wiener Klinische Wochenschrift, 2016, 128: 439-445.

[25] Rolland Y, Dupuy C, van Kan G A, et al. Treatment strategies for sarcopenia and frailty[J]. Medical Clinics, 2011, 95(3): 427-438.

[26] Duan L, Xiao M, Liu S, et al. Associations between modifiable risk factors and frailty progression among individuals with pre-frailty[J]. Experimental Gerontology, 2024, 194: 112494.

[27] Angulo J, El Assar M, Álvarez-Bustos A, et al. Physical activity and exercise: Strategies to manage frailty[J]. Redox biology, 2020, 35: 101513.

[28] Racey M, Ali M U, Sherifali D, et al. Effectiveness of physical activity interventions in older adults with frailty or prefrailty: a systematic review and meta-analysis[J]. Canadian Medical Association Open Access Journal, 2021, 9(3): E728-E743.

[29] Toosizadeh N, Mohler J, Najafi B. Assessing upper extremity motion: an innovative method to identify frailty[J]. Journal of the American Geriatrics Society, 2015, 63(6): 1181-1186.

[30] Bortone I, Sardone R, Lampignano L, et al. How gait influences frailty models and health-related outcomes in clinical-based and population-based studies: a systematic review[J]. Journal of cachexia, sarcopenia and muscle, 2021, 12(2): 274-297.

[31] Greene B R, Doheny E P, O'Halloran A, et al. Frailty status can be accurately assessed using inertial sensors and the TUG test[J]. Age and ageing, 2014, 43(3): 406-411.

[32] Souza D, Vale A F, Silva A, et al. Acute and chronic effects of interval training on the immune system: A systematic review with meta-analysis[J]. Biology, 2021, 10(9): 868.

[33] Andersen L L, Andersen C H, Mortensen O S, et al. Muscle activation and perceived loading during rehabilitation exercises: comparison of dumbbells and elastic resistance[J]. Physical therapy, 2010, 90(4): 538-549.

[34] Farinatti P T V, Geraldes A A R, Bottaro M F, et al. Effects of different resistance training frequencies on the muscle strength and functional performance of active women older than 60 years[J]. The Journal of Strength & Conditioning Research, 2013, 27(8): 2225-2234.

[35] Cadore E L, Casas-Herrero A, Zambom-Ferraresi F, et al. Multicomponent exercises including muscle power training enhance muscle mass, power output, and functional outcomes in institutionalized frail nonagenarians[J]. Age, 2014, 36: 773-785.
[36] Park S, Park S K, Jee Y S. Moderate-to fast-walking improves immunocytes through a positive change of muscle contractility in old women: a pilot study[J]. Journal of exercise rehabilitation, 2023, 19(1): 45.
[37] Ikezoe T, Nakamura M, Shima H, et al. Association between walking ability and trunk and lower-limb muscle atrophy in institutionalized elderly women: a longitudinal pilot study[J]. Journal of physiological anthropology, 2015, 34: 1-6.
[38] Stotz A, Hamacher D, Zech A. Relationship between muscle strength and gait parameters in healthy older women and men[J]. International journal of environmental research and public health, 2023, 20(7): 5362.
[39] Kim H, Park I, joo Lee H, et al. The reliability and validity of gait speed with different walking pace and distances against general health, physical function, and chronic disease in aged adults[J]. Journal of exercise nutrition & biochemistry, 2016, 20(3): 46.
[40] Hayashida I, Tanimoto Y, Takahashi Y, et al. Correlation between muscle strength and muscle mass, and their association with walking speed, in community-dwelling elderly Japanese individuals[J]. PloS one, 2014, 9(11): e111810.
[41] Lim Y P, Lin Y C, Pandy M G. Effects of step length and step frequency on lower-limb muscle function in human gait[J]. Journal of biomechanics, 2017, 57: 1-7.
[42] Watsford M L, Murphy A J, Pine M J. The effects of ageing on respiratory muscle function and performance in older adults[J]. Journal of Science and Medicine in Sport, 2007, 10(1): 36-44.
[43] Huang Y, Meijer O G, Lin J, et al. The effects of stride length and stride frequency on trunk coordination in human walking[J]. Gait & posture, 2010, 31(4): 444-449.
[44] Riviati N, Indra B. Relationship between muscle mass and muscle strength with physical performance in older adults: A systematic review[J]. SAGE Open Medicine, 2023, 11: 20503121231214650.
[45] Research on Speed Control Features of Japanese Women's 1500 m Race. Available online: https://pdf.hanspub.org/APS20210400000_16612551.pdf (accessed on 15 April 2025).
[46] Studenski S, Perera S, Patel K, et al. Gait speed and survival in older adults[J]. Jama, 2011, 305(1): 50-58.
[47] Kutner N G, Zhang R, Huang Y, et al. Gait speed and mortality, hospitalization, and functional status change among hemodialysis patients: a US renal data system special study[J]. American Journal of Kidney Diseases, 2015, 66(2): 297-304.
[48] Barry E, Galvin R, Keogh C, et al. Is the Timed Up and Go test a useful predictor of risk of falls in community dwelling older adults: a systematic review and meta-analysis[J]. BMC geriatrics, 2014, 14: 1-14.
[49] Singh S J, Puhan M A, Andrianopoulos V, et al. An official systematic review of the European Respiratory Society/American Thoracic Society: measurement properties of field walking tests in chronic respiratory disease[J]. European Respiratory Journal, 2014, 44(6): 1447-1478.
[50] Newman A B, Simonsick E M, Naydeck B L, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability[J]. Jama, 2006, 295(17): 2018-2026.

[51] Demir R, Küçükoğlu M S. Six-minute walk test in pulmonary arterial hypertension[J]. Anatolian journal of cardiology, 2015, 15(3): 249.

[52] Wang L, Zhang X, Liu X. Prevalence and clinical impact of frailty in COPD: a systematic review and meta-analysis[J]. BMC Pulmonary Medicine, 2023, 23(1): 164.

[53] Ozalevli S, Ozden A, Itil O, et al. Comparison of the Sit-to-Stand Test with 6 min walk test in patients with chronic obstructive pulmonary disease[J]. Respiratory medicine, 2007, 101(2): 286-293.

[54] Sethi D, Bharti S, Prakash C. A comprehensive survey on gait analysis: History, parameters, approaches, pose estimation, and future work[J]. Artificial Intelligence in Medicine, 2022, 129: 102314.

Chapter 2 Wearable 6MWT measuring system

2.1 Overview

The traditional 6-minute walk test (6MWT) faces many challenges during implementation. Firstly, the test requires multiple examiners to measure each participant, which increases the workload as the number of participants grows. Secondly, the 6MWT typically requires a straight distance course of at least 30m [1, 2], which may be difficult to achieve in some healthcare locations. Additionally, the walking distance is often estimated visually [3, 4], which increases the risk of measurement error, and there is an urgent need for automated measurement technologies to improve accuracy. Currently, the evaluation metrics of the 6MWT mainly focus on the 6-minute walk distance (6MWD) or average walking speed, which do not fully reflect an individual's exercise endurance.

In recent years, with the development of Internet of Things (IoT) technology and the widespread use of wearable sensor devices, monitoring and analyzing walking tests have become increasingly easy and simple [3, 4]. Traditional test methods rely on laboratory environments and use stopwatches and measuring tapes for data collection. Thus, the parameters obtained from these walking tests are limited, which restricts their application in clinical practice. Wearable devices can capture gait signals by placing sensors on different parts of the body, allowing for the measurement of various walking characteristics. Currently, widely used wearable devices include smart wristbands, smart insoles, and sensor-embedded clothing. These devices are equipped with built-in accelerometers, gyroscopes, pressure sensors, and GPS, and can monitor gait parameters in real time [5, 6]. Literature reviews show that inertial accelerometers are the most commonly used sensors in studies related to the 6MWT [7, 8]. Drover et al. used accelerometers to monitor gait data of older adults performing the 6MWT and developed a method for fall classification [9]. To assess physical activity levels in the elderly, Karavirta et al. also used accelerometers to collect 6MWT data [10]. These studies indicate that accelerometers have great potential in gait monitoring and health assessment.

To address the above issues, the main objective of this chapter is to improve the effectiveness of the 6MWT in assessing exercise capacity in older adults. To achieve this, we developed a wearable 6MWT measuring system that uses an accelerometer to automatically collect data and adapt to measurement requirements in various environments. The study also specifically analysed the optimal installation position of the sensors and the parameter calculation method to efficiently obtain detailed data during walking, such as walking speed, step length, and cadence, and visualise them through gait distribution maps. This measuring system not only improves the accuracy of gait analysis but also provides crucial support for the health management and gait optimization in the elderly, thus enhancing its value in daily function assessment, disease management, and health monitoring in this population.

2.2 Wearable accelerometers

The wearable device includes a 3-axis TWELITE accelerometer sensor unit (Mono Wireless, Japan) and a 3V button cell battery, as shown in Figure 2.1. The device has dimensions of 20×20×10 mm, a weight of 6.5 g, a sampling rate of 50 Hz, and a measurement range of -16 g~+16 g. It is designed for good wearability and can effectively support walking monitoring requirements.

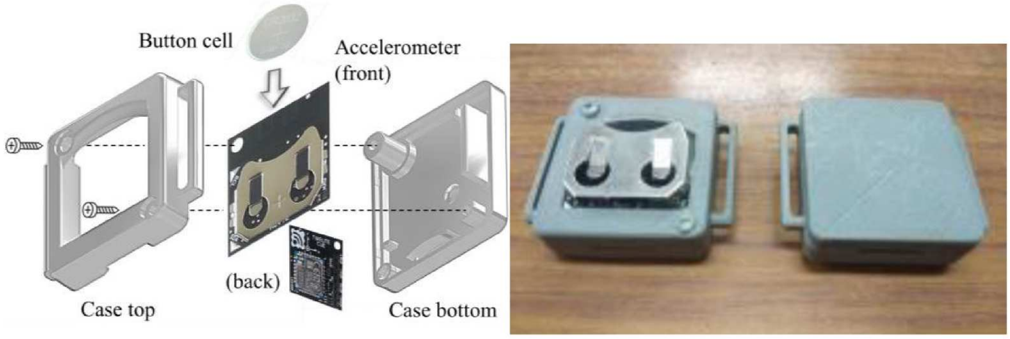


Figure 2.1 Schematic diagram of a wearable accelerometer.

In clinical and functional movement assessment studies, the motion characteristics of different body parts reflect different biomechanical information [11]. Therefore, the placement of the sensor has a significant impact on the accuracy and representativeness of the data. Generally, head movements mainly reflect upper body posture control and balance, which are important for evaluating overall stability and nervous system regulation [12]. The waist, being close to the body's center of gravity, is a key location for monitoring trunk stability and overall body displacement [13]. The ankle, which is directly involved in gait propulsion, contains more detailed information about lower limb movements, such as step length (SL), step cadence (SC), and swing phase [14]. Therefore, in this study, wearable accelerometer sensors were placed on three representative body parts: the head, waist, and ankle, to enable dynamic monitoring of elderly walking patterns, as shown in Figure 2.2.

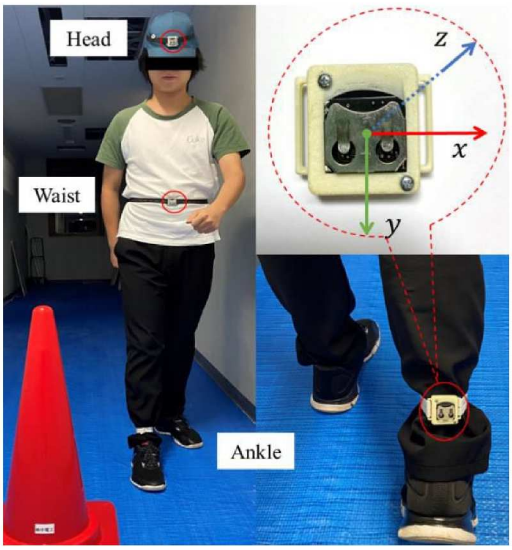


Figure 2.2 Schematic diagram of sensors worn on the head, waist, and ankle using elastic bands (Installation method at the ankle Location, Downward: positive y-axis; Forward: positive z-axis; Rightward: positive x-axis).

2.3 Suitable for various 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 2.3 depicts a system suitable for fixed application settings such as medical institutions, rehabilitation centers, and nursing homes, where data is transmitted quickly and continuously over Wi-Fi, enabling multi-person gait tests and compatibility with other clinical equipment. The system consists of an accelerometer sensor, a DIP-WiFi signal repeater, a Wi-Fi router, and a data analysis management server. Specifically, the accelerometer sensor wirelessly transmits the collected gait data to the signal repeater. The repeater receives the signal through the TWELITE DIP and converts it into a Wi-Fi signal via serial communication, which is then uploaded to the server using an XbeeWiFi device.

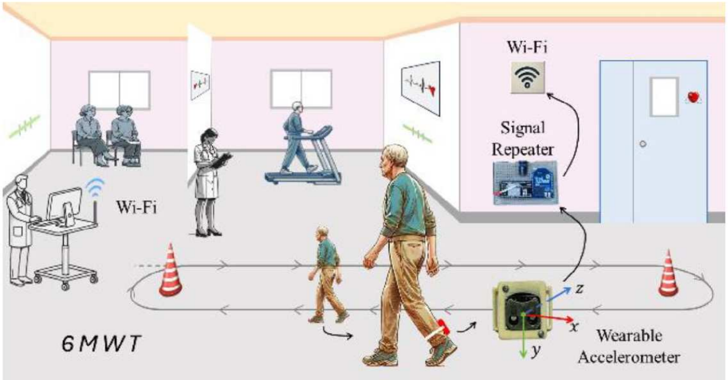


Figure 2.3 A data collection method using Wi-Fi.

Figure 2.4 depicts an outdoor scenario, where the device wirelessly connects the accelerometer sensor with a small TWELITE DIP signal receiver attached to the USB port of a smartphone, facilitating quick data collection of gait data and generation of test results.

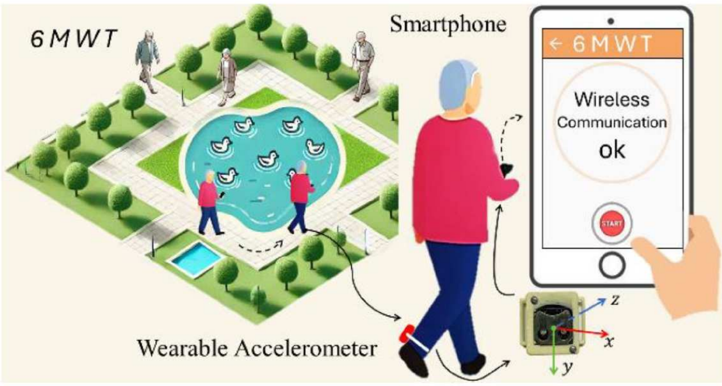


Figure 2.4 A data collection method using smartphone.

To evaluate the stability and reliability of the walking test system in real-world applications, we compared the total number of data points collected by the sensor during the 6MWT with the theoretical number of sampling points. The results showed that both data transmission methods achieved a signal reception success rate of over 95%, providing a reliable data foundation for subsequent gait analysis.

2.4 Experiment: six-minute walk test (6MWT)

Since motion patterns vary across body parts, the acceleration signal differs significantly based on sensor placement [11]. 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 2.2), and participants were instructed to walk for 6 minutes on a standardized track, as shown in Figure 2.5 [1, 2]. According to the 6MWT testing guidelines, participants started from the left-side cone and walked back and forth along the designated routes A, B, C, and D as quickly as possible, where A, C were straight walking courses and B, D were U-turn walking courses. Due to the guidelines requiring that the sum of the distances of the straight-line course in a walking circumference is greater than 30m, here we set the distance between two cones to 20 meters, with a marker placed every meter to facilitate simple calculation of the walking distance [1, 2].

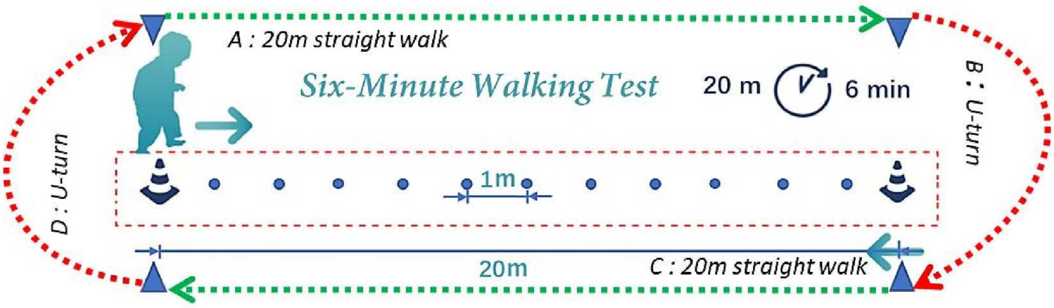


Figure 2.5 Schematic diagram of the six-minute walk test (6MWT).

2.5 Gait acceleration data

Figure 2.6 shows on the left side a portion of the acceleration data collected by sensors at different body locations during walking. From top to bottom, the signals are from the head, waist, and ankle. Each sensor recorded acceleration data in three directions. The right side shows a magnified view of the data from the left side.

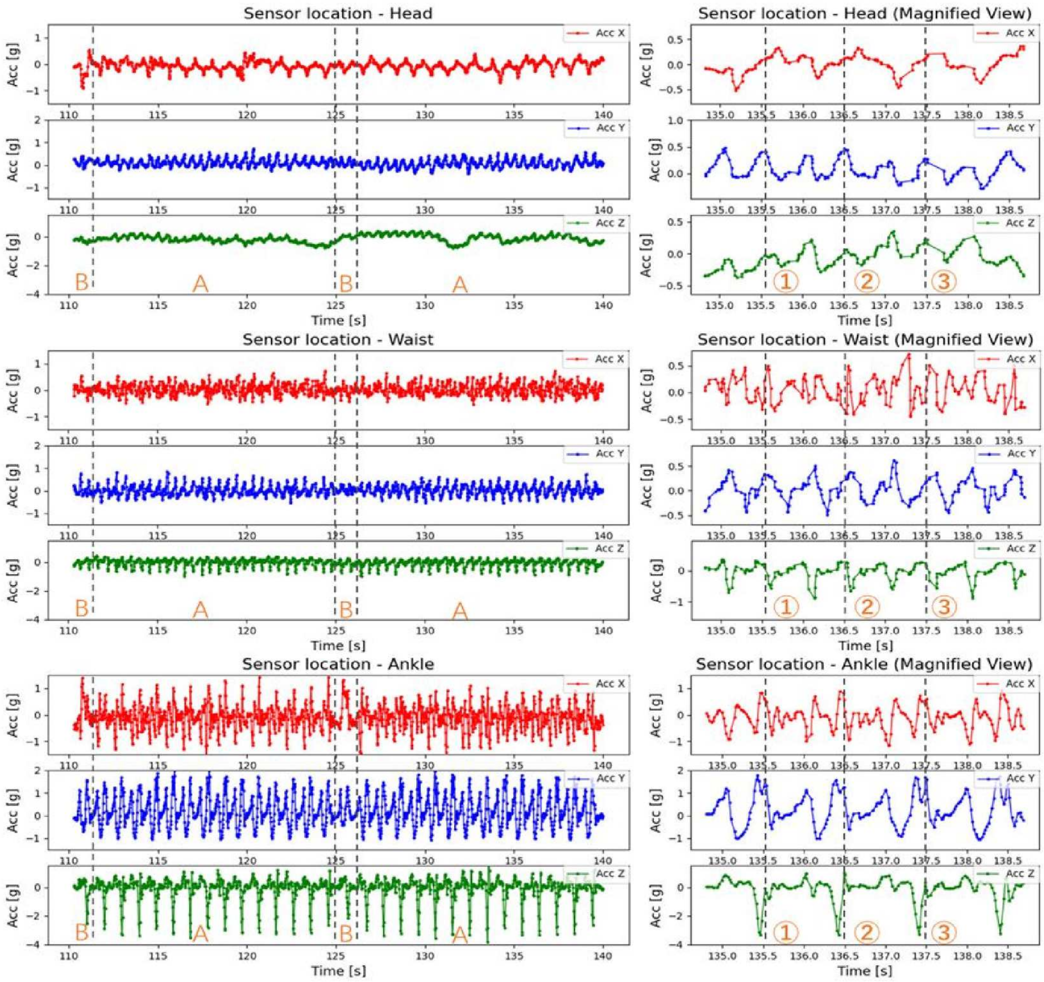


Figure 2.6 A portion of the acceleration data collected from sensors at the head, waist, and ankle during 6MWT.

2.5.1 Straight walking and U-turn walking

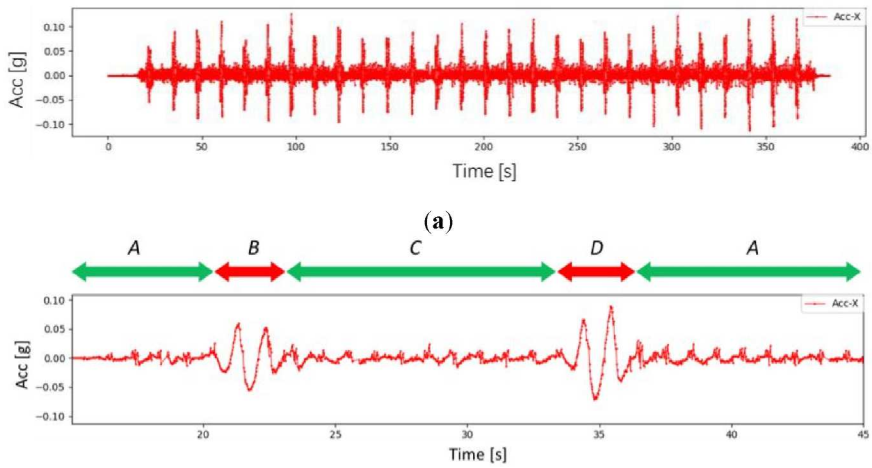
In clinical practice, medical staff usually record only the 20m straight walking distance based on the walking path shown in Figure 2.5, while the turning sections are often ignored. Therefore, distinguishing between 20m straight walking and U-turn walking is the first step in data analysis. We used the characteristic that the acceleration on the x-axis of the ankle sensor increases sharply during U-turn walking, and marked sections A and B in the left part of Figure 2.6 (left) to indicate straight walking and U-turn walking. Furthermore, we applied an Infinite Impulse Response (IIR) low-pass filter as Equation (2.1), to the x-axis signal of the ankle to preprocess the data.

$$x_g(t) = \alpha_0(x(t)\beta_0 + x(t-1)\beta_1 + x(t-2)\beta_2 - x_g(t-1)\alpha_1 - x_g(t-2)\alpha_2) \tag{2.1}$$

In Equation (2.1), α_0, α_1, α_2, β_0, β_1 and β_2 were the filter coefficients. We computed these coefficients using a second-order Butterworth low-pass filter as Equation (2.2), where the normalized cutoff frequency was calculated as $w_c = 2f_c/f_s$ (with a cutoff frequency $f_c = 0.2\ [Hz]$ and a sampling frequency $f_s = 0.2\ [Hz]$).

$$\begin{cases} \alpha_0 = 1, \alpha_1 = \dfrac{2(1 - w_c^2)}{w_c^2}, \alpha_2 = \dfrac{\left(\sqrt{2}w_c - w_c^2 - 1\right)}{w_c^2} \\ \beta_0 = 1, \beta_1 = 2, \beta_2 = 1 \end{cases} \tag{2.2}$$

Figure 2.7(a) shows the overall result after filtering, and Figure 2.7(b) shows a magnified view. It can be observed that this characteristic becomes more distinct; based on this feature, we can distinguish between the 20m straight walking sections and the U-turn walking sections during the 6MWT.



(a)

(b)

Figure 2.7 X-axis acceleration data after low-pass filtering: (a) shows the entire 6MWT process, and (b) shows the characteristics of the magnified straight walking and U-turn walking section.

2.5.2 Gait cycle

In gait analysis, identifying gait cycles within continuous walking signals is extremely important, as it serves as the basis for analyzing spatiotemporal gait parameters such as SL, SC, and walking speed. According to the gait kinematic analysis shown in Figure 2.8, each foot strike is generally considered the starting point of a gait cycle. Therefore, in Figure 2.6 (right), we marked the start and end waveforms of two gait cycles at time points ①, ②and ③ based on the characteristic reaction force from the ground on the foot, reflected in the acceleration signal from the ankle during foot contact [15].

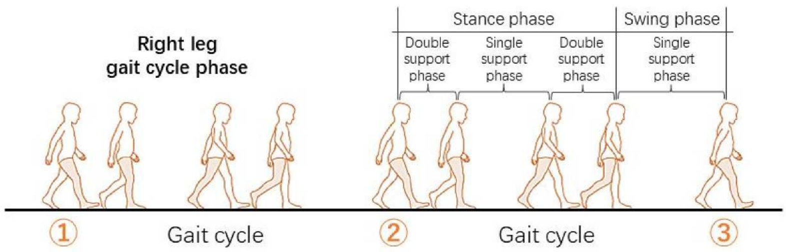


Figure 2.8 Gait kinematic analysis

2.6 Results and discussion

2.6.1 Feasibility analysis

In the field of signal processing, a simple method for determining periodicity is to apply the Fast Fourier Transform (FFT) [16], as Equation (2.3), because it allows gait data to be converted from the time domain to the frequency domain, making it easier to identify walking cycles and frequency characteristics. Since the x-axis signal has poor periodicity, Figure 2.9 shows the results of applying the FFT to the y-axis and z-axis signals from the head, waist, and ankle.

$$F(t) = \sum_{y=0}^{N-1} f(y) exp\,(-i\frac{2\pi ty}{N}) \tag{2.3}$$

According to the gait cycle diagram on the right side of Figure 2.6, by detecting the peak in the ankle accelerometer signal at the moment the foot contacts the ground, it is also easy to manually calculate the time of each step. The resulting average SC is 2.13^{-1} [s/step], which is almost the same as the result obtained by applying FFT to the waist and ankle accelerometer signals. In addition, FFT analysis shows that the signals from the waist and ankle contain more frequency components, with the ankle providing the most gait-related information. However, the sensor data from the head only contains one main frequency component, which represents the head's swinging cycle during walking.

Although the head signal can reflect the walking cycle and even balance status, and the waist signal can show the movement of the body's center of gravity, the small amplitude of acceleration brings some difficulty to further gait analysis. At the same time, we observed the clinical testing process and found that it is difficult for participants to maintain continuous focus while walking. The head is easily disturbed by the environment and swings irregularly, while the waist signal is affected by clothing, rapid breathing, and abdominal muscle contractions, leading to unstable changes in the time-series signal. To remove these effects, more complex signal processing techniques may be required. In comparison, the sensor placed at the ankle is likely more suitable for gait analysis, as it allows for easier extraction of walking-related features.

Table 2.1 presents the difficulty of extracting gait parameters in gait kinematics, phase, and kinetics, where "O" 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 2.6 (right), leading to unclear segmentation of the 20m straight-line walking parts, further affecting the calculation of the walking distance, SL (calculated 20m divided by step count), and walking speed (calculated the product of SL and SC). 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.

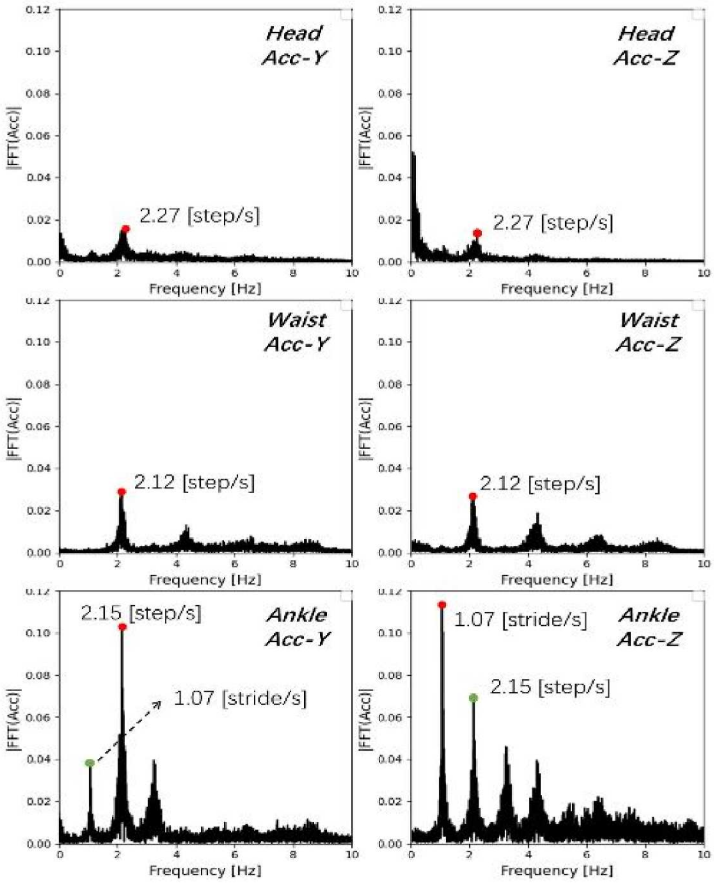


Figure 2.9 FFT analysis results of the y-axis and z-axis from the head, waist, and ankle signals, with step time corresponding to 2.27^{-1}, 2.12^{-1}, and 2.15^{-1} [s/step], respectively, for the main frequency components.

Table 2.1 Difficulty in Extracting Gait Parameters.

	Kinematic Parameters					Phase Parameters			Kinetic Parameters	
	Step Count	SL	SC	Walking Distance	Walking Speed	Gait Cycle	Stance Phase	Swing Phase	Y-axis Acceleration	Z-axis Acceleration
Head	O	△	O	△	△	△	–	–	–	–
Waist	O	△	O	△	△	△	–	–	–	–
Ankle	O	O	O	O	O	O	O	O	O	O

Note, "O": Easy; "△": Difficult; "–": Unclearly obvious.

2.6.2 Gait characteristics

With the above analysis, we focused on analyzing the ankle signals to extract gait features. Figure 2.10 shows the kinematic characteristics and gait phases of the y-axis and z-axis data at the ankle, where the marks ①, ②and ③ correspond to the three states in Figure 2.6 (left). 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.

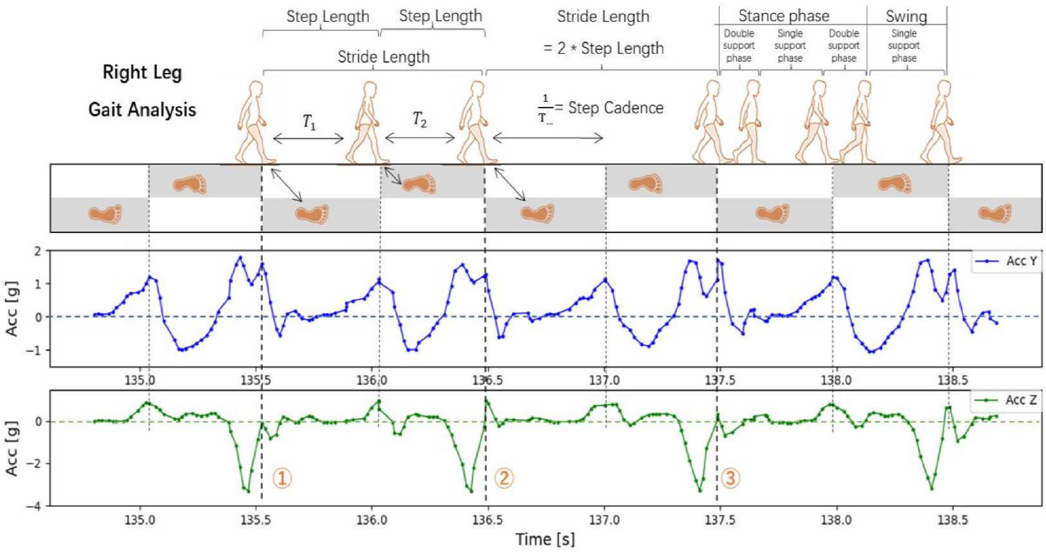


Figure 2.10 Kinematic characteristics and gait phases of the y-axis and z-axis in ankle signals. One point to note, Stride length $= 2 \times$ Step length.

Figure 2.10 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 [17], while the duration and ratio of the support phase and swing phase reflect the balance and stability of gait [18].

2.6.3 Clinical applications

2.6.3.1 Overview

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 [19]. The total distances at 300 and 400 meters are usually regarded as key thresholds, where a 6MWD above 400 meters tends to indicate good cardiorespiratory function and Physical activity ability outside the home [20], while below 300 meters may be in higher risk of disease and mortality for older adults [21].

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 300 and 400 meters 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.

2.6.3.2 Participants

We recruited 60 elderly participants (46 males and 14 females, age 72 ± 5 years, weight 63 ± 12 kg, height 163 ± 8 cm) from August 2021 to July 2022 at the university-affiliated hospital as our study sample. These participants had basic physical activity capabilities and no diseases that would affect their ability to complete the assessments in this study. Before the experiment, the research staff explained the study protocol to the participants and obtained their written informed consent. This research project was approved by the local (Ube, Japan) Institutional Review Board (No. H2021-031).

2.6.3.3 Gait parameters

We collected 6MWT gait data from 60 elderly participants with normal walking ability. Four gait parameters, namely step length (SL), step cadence (SC), gait velocity (GV), and six-minute walking distance (6MWD) were extracted and calculated as follows.

(1) Step Length (SL)

SL [m/step] is the length during one action of lifting and placing the same foot [17]. Figure 2.11 shows the results of the kinematic analysis of acceleration data in the up-down direction during each straight walking part. Since the distance of each straight walking part is 20 meters, we only need to determine the number of steps to calculate SL by Equation (2.4).

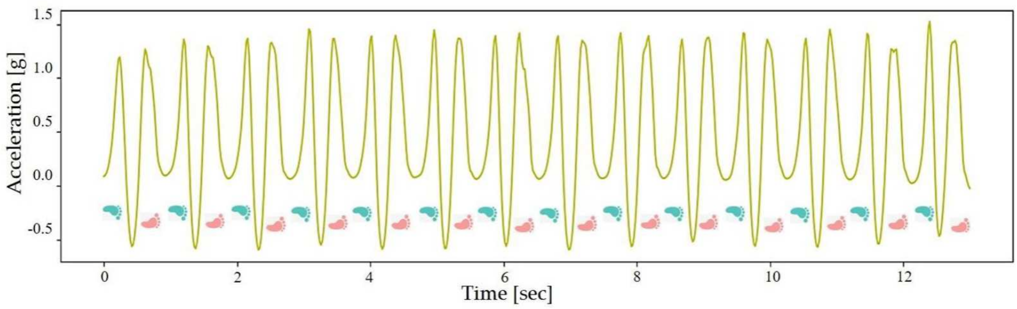


Figure 2.11 Analysis results of the y-axis (up-down direction) acceleration data for a straight walking part.

$$SL = \frac{20m}{step} \tag{2.4}$$

Generally, SL is correlated with height. However, this study found a low correlation between SL and height. We believe that this may be due to the 'walk as far as possible' instruction in the 6MWT or the participants were mostly elderly patients with respiratory diseases.

(2) Step Cadence (SC)

SC [step/s] is the beat of walking and the number of steps per second [17]. We applied the Fast Fourier Transform (FFT) to the acceleration data of each straight walking part and obtained the frequency component in Figure 2.12. In the spectrum diagram, the frequency component corresponding to the maximum amplitude represents the mean SC of this straight walking part.

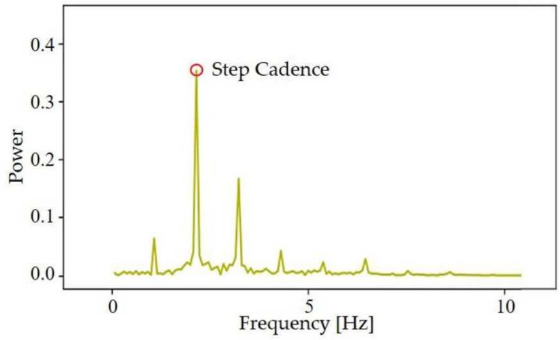


Figure 2.12 FFT analysis of each y-axis straight walking data (up-down direction). The average step cadence (SC) is the frequency value corresponding to the maximum peak.

(3) Gait Velocity (GV)

GV [m/s] is the product of SL and SC [17] as shown in Equation (2.5). SL and SC are the averages of the straight walking parts.

$$GV = SL * SC \tag{2.5}$$

(4) Six-Minute Walking Distance (6MWD)

According to the 6MWT test guidelines, 6MWD [m] is the sum of all straight parts distances in 6 minutes. Our calculation method is to add the distance of the complete straight parts, plus the final estimated partial straight distance, as shown in Equation (2.6).

$$6MWD = 20 * p + SL * q \tag{2.6}$$

Where p is the number of complete straight walking, SL is the mean value calculated by Equation (2.4), and q is the number of steps recognized in the final straight partial.

2.6.3.4 Results and discussion

Linear regression analysis showed that the 6MWD calculated in this study was highly correlated with the distance recorded by the medical staff ($y = 1.00 * x + 1.28, r = 0.99$). However, we found that there were some errors in the medical staff's records, such as missing one lap for some participants.

Figure 2.13 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 1.33 [m/s] and the red dashed line represents 1.00 [m/s]. Two thresholds were derived from a linear regression analysis of 6MWD with gait speed ($y = 286.77 * x + 18.90, r = 0.98$), corresponding to walking distances of 400m and 300m, respectively.

It should be noted that the 6MWD is not simply the product of speed and time, as the test includes several U-turns, and the 6MWD reflects only the total distance of all straight-line walking parts.

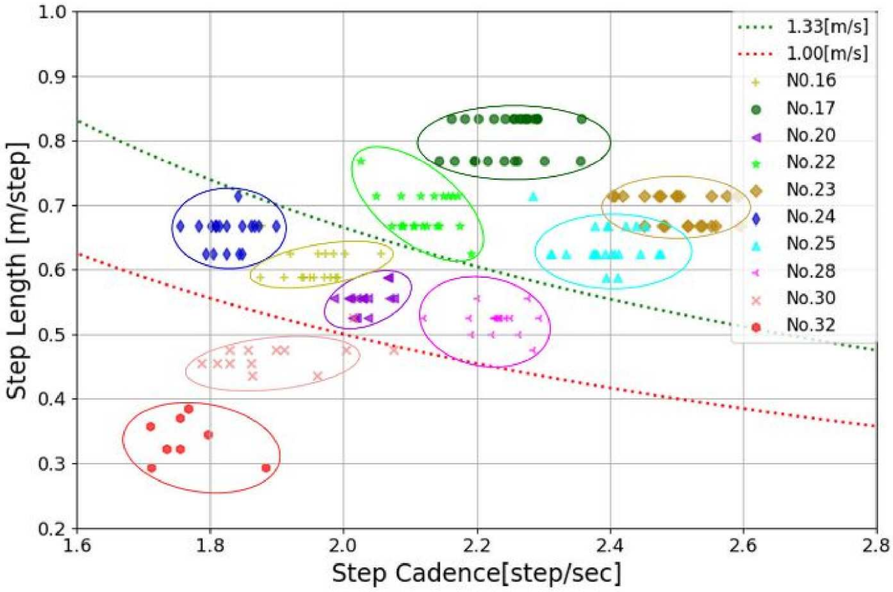


Figure 2.13 The gait distribution map of 10 elderly people.

This distribution map can efficiently and quickly obtain detailed data on walking speed, step length, and step cadence in the 6MWT. It 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.

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 SC or SL 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.

2.7 Health record system

Figure 2.14 shows the 6MWT health record system we developed, which integrates data collection, automated analysis, and management. This system allows healthcare professionals to monitor and systematically manage walking data in older adults, helping them better understand changes in physical condition and providing support for creating personalized intervention plans. It plays an important role in the management of age-related diseases. In addition, the system also allows users to check their own 6-minute walking status and automatically adjust their walking plans, helping to maintain and improve muscle function.

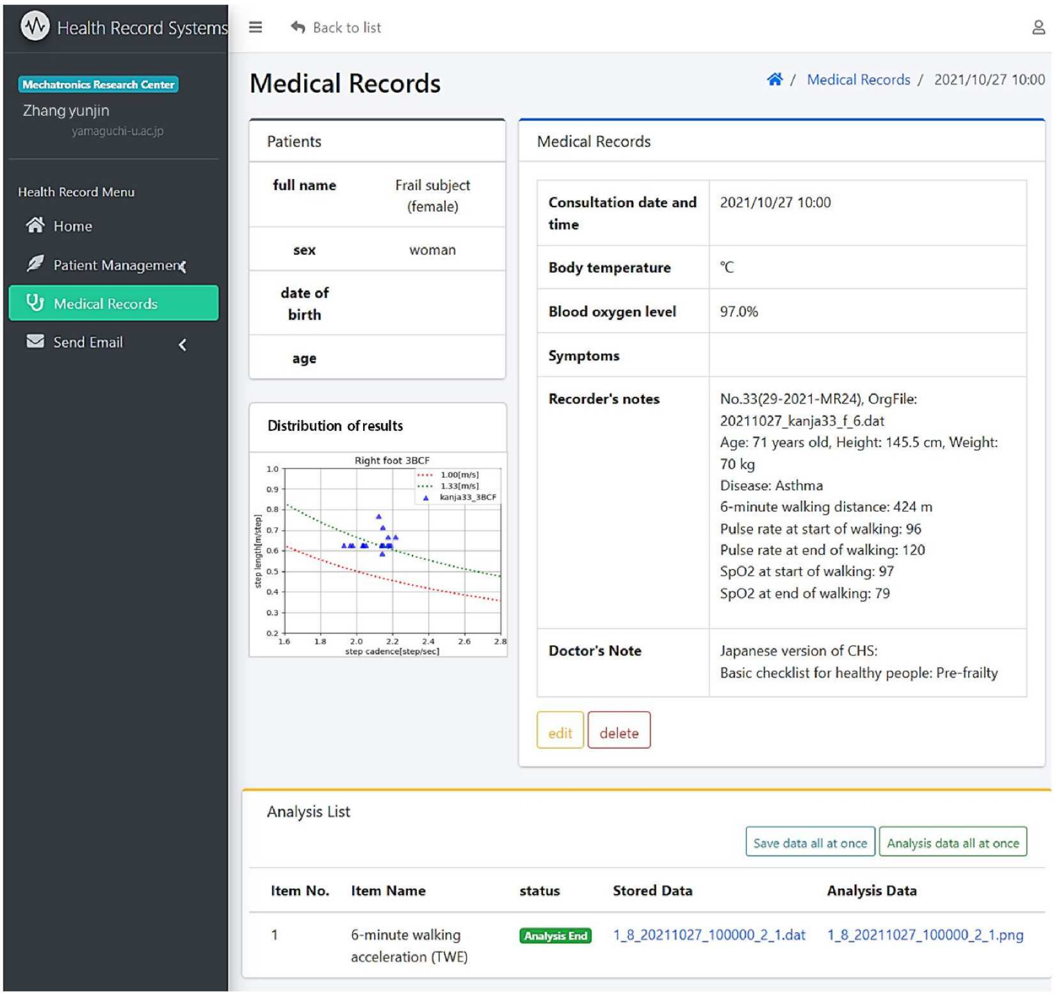


Figure 2.14 Health Record System

2.8 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, based on the relationship between distance and speed, for providing richer information about physical health and expanding the depth and breadth of the health management of the elderly.

References

[1] ATS. Committee on Proficiency Standards for Clinical Pulmonary Function Laboratories, ATS Statement[J]. American Journal of Respiratory and Critical Care Medicine, 2002, 166(1): 111-117.

[2] Enright P L. The six-minute walk test[J]. Respiratory care, 2003, 48(8): 783-785.

[3] Yeo J C, Lim C T. Emerging flexible and wearable physical sensing platforms for healthcare and biomedical applications[J]. Microsystems & Nanoengineering, 2016, 2(1): 1-19.

[4] Mamdiwar S D, Shakruwala Z, Chadha U, et al. Recent advances on IoT-assisted wearable sensor systems for healthcare monitoring[J]. Biosensors, 2021, 11(10): 372.

[5] Huang C, Nihey F, Ihara K, et al. Healthcare application of in-shoe motion sensor for older adults: Frailty assessment using foot motion during gait[J]. Sensors, 2023, 23(12): 5446.

[6] Scherrenberg M, Bonneux C, Yousif Mahmood D, et al. A mobile application to perform the six-minute walk test (6MWT) at home: a random walk in the park is as accurate as a standardized 6MWT[J]. Sensors, 2022, 22(11): 4277.

[7] Storm F A, Cesareo A, Reni G, et al. Wearable inertial sensors to assess gait during the 6-minute walk test: A systematic review[J]. Sensors, 2020, 20(9): 2660.

[8] Godinho C, Domingos J, Cunha G, et al. A systematic review of the characteristics and validity of monitoring technologies to assess Parkinson's disease[J]. Journal of neuroengineering and rehabilitation, 2016, 13: 1-10.

[9] Drover D, Howcroft J, Kofman J, et al. Faller classification in older adults using wearable sensors based on turn and straight-walking accelerometer-based features[J]. Sensors, 2017, 17(6): 1321.

[10] Karavirta L, Rantalainen T, Skantz H, et al. Individual scaling of accelerometry to preferred walking speed in the assessment of physical activity in older adults[J]. The Journals of Gerontology: Series A, 2020, 75(9): e111-e118.

[11] Amini N, Sarrafzadeh M, Vahdatpour A, et al. Accelerometer-based on-body sensor localization for health and medical monitoring applications[J]. Pervasive and mobile computing, 2011, 7(6): 746-760.

[12] Allum J H J, Gresty M, Keshner E, et al. The control of head movements during human balance corrections[J]. Journal of Vestibular Research, 1997, 7(2-3): 189-218.

[13] Tesio L, Rota V. The motion of body center of mass during walking: a review oriented to clinical applications[J]. Frontiers in neurology, 2019, 10: 999.

[14] Neptune R R, Kautz S A, Zajac F E. Contributions of the individual ankle plantar flexors to support, forward progression and swing initiation during walking[J]. Journal of biomechanics, 2001, 34(11): 1387-1398.

[15] Sinclair J, Hobbs S J, Protheroe L, et al. Determination of gait events using an externally mounted shank accelerometer[J]. Journal of applied biomechanics, 2013, 29(1): 118-122.

[16] Mummolo C, Mangialardi L, Kim J H. Quantifying dynamic characteristics of human walking for comprehensive gait cycle[J]. Journal of biomechanical engineering, 2013, 135(9): 091006.

[17] Lim Y P, Lin Y C, Pandy M G. Effects of step length and step frequency on lower-limb muscle function in human gait[J]. Journal of biomechanics, 2017, 57: 1-7.

[18] Umberger B R. Stance and swing phase costs in human walking[J]. Journal of the Royal Society Interface, 2010, 7(50): 1329-1340.

[19] Singh S J, Puhan M A, Andrianopoulos V, et al. An official systematic review of the European Respiratory Society/American Thoracic Society: measurement properties of field walking tests in chronic respiratory disease[J]. European Respiratory Journal, 2014, 44(6): 1447-1478.

[20] Newman A B, Simonsick E M, Naydeck B L, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability[J]. Jama, 2006, 295(17): 2018-2026.

[21] Demir R, Küçükoğlu M S. Six-minute walk test in pulmonary arterial hypertension[J]. Anatolian journal of cardiology, 2015, 15(3): 249.

Chapter 3 Evaluation of lower limb muscle status and physical frailty

3.1 Overview

A study of Japanese community-dwelling older people 65 years of age and older by Kojima et al. reported that the overall prevalence of frailty and pre-frailty was 7.4% and 48.1%, respectively [1]. Considering that Japan is one of the countries with the longest life expectancy and a large aging population, more than half of its older adults experience symptoms of frailty or pre-frailty. This seriously challenges social support, healthcare services, and long-term care systems. Frailty is defined as the body's reduced ability to adapt to and recover from external stresses such as illness, surgery, or injury, and is characterized by a general decline in physical function, cognitive ability, and physiological reserve [2]. Frailty is considered to be an intermediate stage between health and disability [2, 3] as shown in Figure 3.1. Importantly, frailty is not merely a consequence of aging; rather, it reflects increased vulnerability caused by the simultaneous decline of multiple body systems, making individuals more likely to suffer serious health outcomes even from minor stressors [1, 3, 4] .

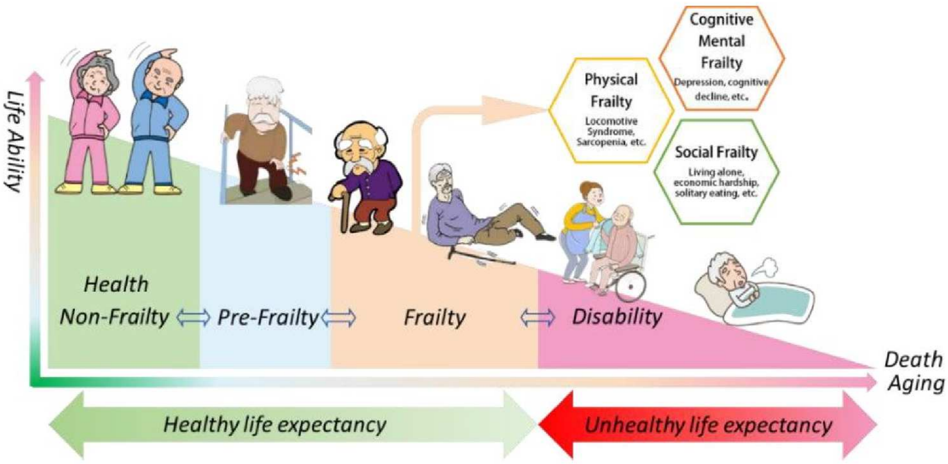


Figure 3.1 Schematic diagram of frailty

When frailty progresses to a more severe stage, individuals often lose basic mobility functions, such as the ability to walk independently, stand up, or maintain balance, which may result in disability. This not only indicates a significant decline in physical function but also marks the boundary between healthy life expectancy and unhealthy life expectancy [5]. Healthy life expectancy refers to the number of years a person can live independently without major functional impairments, while unhealthy life expectancy refers to the years spent with reduced quality of life or dependence on others for daily care [6, 7]. The loss of mobility often signifies the end of healthy life and the beginning of unhealthy life, leading to a loss of self-care ability, increased demand for medical resources, and a significant decrease in quality of life. Therefore, preventing or delaying frailty and the associated loss of mobility is essential for extending healthy life expectancy, reducing the duration of unhealthy life, and improving the quality of life in older persons.

Frailty poses a serious threat to the daily life of older adults, and many researchers have proposed different methods for assessing frailty. The frailty assessment model proposed by Fried et al. in 2001 is currently the most widely used method, with its data originating from the Cardiovascular Health Study (CHS) [8]. In the 1990s, Fried and colleagues conducted a secondary analysis of a prospective cluster study involving 5,210 men and women aged 65 years and older, and established criteria for identifying frailty. Fried et al.'s method is a well-known, phenotype-based screening standard that has been widely accepted and used globally. However, the study population used in their research was recruited from European countries, and the thresholds for identifying frailty may not be suitable for Asian populations.

In 2014, Arai Hideno and colleagues from the Japan Geriatrics Society proposed the J-CHS model [9], which is suitable for the Japanese population, as shown in Table 3.1. This model evaluates frailty based on five items: unconscious weight loss, self-reported exhaustion, decreased physical activity, decreased muscle strength (handgrip strength; HS), and reduced physical performance (walking speed; WS). Among them, unconscious weight loss, self-reported exhaustion, and reduced physical activity are assessed subjectively through a questionnaires. HS and WS are evaluated through physical tests. The assessment criteria for HS and WS follow the standards defined by the Asian Working Group for Sarcopenia (AWGS) [10]. The threshold for HS is 28 kg for men and 18 kg for women, while the WS threshold for both men and women is 1.0 m/s. HS is calculated as the average of three measurements for each hand, and WS is measured by timing how long it takes to walk 5m using a stopwatch.

Table 3.1 Japanese version of the frailty assessment criteria (J-CHS).

Items	**Assessment Criteria**
(1) Weight Loss (WL)	Questionnaires: (Yes = 1, No = 0) Have you lost 2 kg or more in the past 6 months?
(2) Exhaustion (EX)	Questionnaires: (Yes = 1, No = 0) In the past 2 weeks, have you felt tired without a reason?
(3) Physical Activity (PA)	Questionnaires: ("No" to both questions = 1, others = 0) Do you engage in moderate levels of physical exercise or sports aimed at health? Do you engage in low levels of physical exercise aimed at health?
(4) Handgrip Strength (HS)	Clinical test: (Yes = 1, No = 0) Men: <28 kg, Women: <18 kg
(5) Walking Speed (SP)	Clinical test: (Yes = 1, No = 0) Speed < 1.0 m/s (obtained by five-meter walking test)

According to the J-CHS criteria, each item is counted as one point, with a total score of n = 5. A score of $n \geq 3$ indicates frailty, $n \leq 2$ indicates pre-frailty, and $n = 0$ indicates non-frailty. The three conditions are described as follows:

(1) Healthy/Non-frail state: Refers to individuals with intact functions and good adaptability, who can maintain stability and self-repair when facing environmental changes or illnesses.

(2) Pre-frail state: Represents a transitional stage between health and frailty. Individuals may experience slight physical decline, reduced endurance, or decreased activity, but have not yet developed obvious functional impairments.

(3) Frail state: Indicates significant decline in multiple system functions, with symptoms such as reduced physical activity, increased risk of falling, obvious fatigue, and unconscious weight loss.

There is a dynamic relationship among these three states. Healthy individual may gradually shift into a pre-frail state due to aging, chronic diseases, poor lifestyle habits, or changes in the social environment. If appropriate interventions, such as exercise, nutrition management, or medical treatment, are introduced at this stage, the individual may return to a healthy state. On the other hand, without timely intervention, pre-frailty is highly likely to progress into frailty. Although reversing frailty is more difficult once it has developed, some individuals may still improve to a pre-frail or healthy state through comprehensive interventions, including rehabilitation and social support.

In clinical practice, interventions for frailty in older adults mainly focus on resistance training and nutritional supplementation [11, 12, 13]. Although studies have shown that these methods can be effective, it does not mean that all frail individuals can recover to a pre-frail or fully healthy state. Frailty is a multidimensional condition that can generally be divided into physical frailty, psychological or mental frailty, and social frailty [14]. Among, physical frailty is considered the most critical type and often serves as the foundation for the worsening of other types. This is because physical frailty is usually caused directly by a decline in muscle function, such as reduced lower limb strength, walking difficulties, and impaired balance. These physical limitations restrict activity and indirectly lead to feelings of isolation, depression, and reduced social engagement, contributing to psychological and social frailty. In contrast, psychological and social frailty are often triggered by weight loss, fatigue, or reduced physical activity. These conditions tend to be more reversible and responsive to interventions such as psychological counseling, encouragement of social interaction, and participation in activities.

Therefore, accurately identifying physical frailty caused by muscle function decline is crucial for slowing down the progression of frailty. Walking, as a basic activity, is not only a means of mobility but also a core activity essential for maintaining musculoskeletal and cardiovascular health. Research has shown that walking plays an important role in preventing muscle function decline and musculoskeletal disorders [15]. Clinically, the 6-minute walking test (6MWT) requires participants to walk as fast as possible within 6 minutes, which is closely related to the J-CHS criteria for the assessment items such as physical activity, exhaustion, and walking speed, suggesting the possibility of the 6MWT replacing the J-CHS. Additionally, the J-CHS criteria rely too much on questionnaires, and as a semi-objective assessment method, they may not accurately identify physical frailty due to muscle decline. Specifically, the use of 1m/s as a cut-off value for walking speed and the reliance on subjective perception to assess physical fatigue and activity, suggest that this method lacks sufficient objectivity.

This chapter aims to explore whether objective data from the 6MWT can supplement the subjective metrics in the J-CHS criteria and evaluate the feasibility of using walking data to assess frailty. The study analyses the key indicators from the 6MWT and compares them with the five items in the J-CHS criteria to explore a more objective method for determining frailty. Based on these analyses and combining the functional characteristics of muscle fibers, gait patterns related to the decline of muscle function are identified, a new method for assessing physical frailty is proposed, and its effectiveness is validated through the J-CHS criteria. The goal is to provide a more objective and accurate tool for frailty assessment, thereby optimizing health management in the elderly.

3.2 Methods

3.2.1 Participants

Consistent with the description in Chapter 2, we recruited 60 elderly participants from the university-affiliated hospital as the sample data.

3.2.2 Experimental process

(1) After signing the informed consent form, participants provided relevant information (such as gender, age, weight, and height) through a brief interview.

(2) We assessed frailty in all participants using the J-CHS evaluation method (Table 3.1).

(3) According to the 6MWT guidelines (Figure 2.5) [16, 17], the 60 elderly participants were instructed to walk as fast as possible for six minutes on a standardized track. Medical staff gave time reminders every minute and encouraged the participants throughout the test.

3.2.3 Statistical Analysis

We used the Shapiro–Wilk test to check whether the variables obeyed the normal distribution. The Student's t-test was used for the two groups' data that conformed to a normal distribution, and the ANOVA analysis was used for the data that did not conform to a normal distribution. We compared differences in the gait parameters among clinical diagnostic results (frail, pre-frail, and non-frail) and calculated the p-values to determine the significance of these differences. For some statistical tests, the mean value and standard deviation were reported, and p-values less than 0.05 were considered to be statistically significant. In addition, we calculated Cohen's d effect size (d-value) to supplement the assessment of the practical impact of these differences, where d-values = 0.2, 0.5, and 0.8 were considered small, medium, and large effects. Combining the significance and effect size, we explored the significance of the gait parameters in frailty.

We performed receiver operating characteristic (ROC) analyses on the basic gait parameters to explore their role in the frailty assessment. Among the independent predictor variables, an area under the curve (AUC) of the ROC analysis greater than 0.7 was considered statistically significant, and its corresponding threshold was often used to develop differentiation models.

3.3 Results

3.3.1 Participants and frailty evaluation

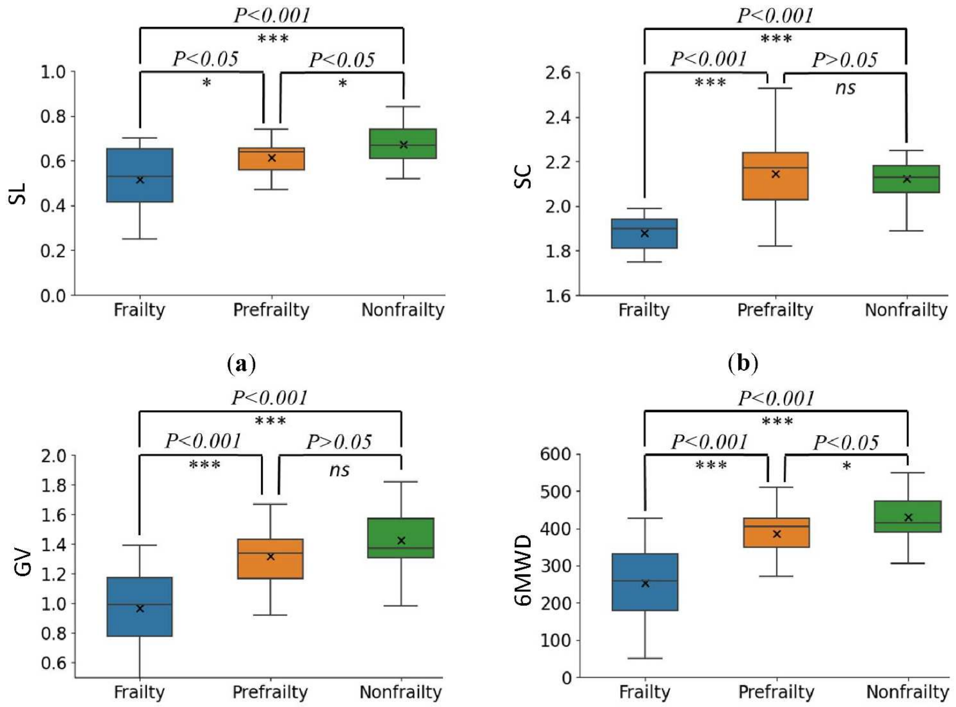
This study recruited 60 older adults and collected their basic personal information. Participants were classified based on the J-CHS frailty evaluation criteria. Among them, 13.4% were identified as frail, 38.3% were in a pre-frail state, and 48.3% were categorized as non-frail. Table 3.2 presents detailed information about the participants. Comparison of the three groups showed that with increasing frailty severity, the average age of participants tended to increase, while average grip strength and walking speed decreased. In the frail group, the proportion of participants who did not meet the J-CHS criteria was as follows: unintentional weight loss (50%), fatigue (75%), low physical activity (75%), low grip strength (75%), and slow walking speed (62.5%). These findings are consistent with the definition of frailty, indicating that as age increases, multiple physical functions tend to decline, and older adults in a frail state often do not meet the standards in several aspects.

Table 3.2 Participant demographic characteristics and frailty assessment in the J-CHS.

Characteristic	Frail, n = 8 (13.4%)	Pre-Frail, n = 23 (38.3%)	Non-Frail, n = 29 (48.3%)
Male,(Female)	7 (1)	18 (5)	21 (8)
Age, mean ± sd	78.38 ± 5.5	70.87 ± 8.02	70.21 ± 6.49
Height, cm, mean ± sd	159.38 ± 7.22	163.87 ± 7.4	163.84 ± 8.06
Weight, kg, mean ± sd	52.7 ± 12.42	67.27 ± 11.37	63.3 ± 10.71
Body mass index, kg/m2, mean ± sd	20.64 ± 4.07	24.99 ± 3.67	23.64 ± 3.98
Average handgrip strength, kg, mean ± sd	22.65 ± 5.89	28.13 ± 7.62	32.42 ± 6.83
5 m walking speed, m/sec, mean ± sd	0.96 ± 0.3	1.25 ± 0.24	1.36 ± 0.18
Observed J-CHS Criteria, n (%)			
Weight loss (WL)	4 (50%)	5 (21.7%)	0 (0)
Exhaustion (EX)	6 (75%)	7 (30.4%)	0 (0)
Physical activity (PA)	6 (75%)	11 (47.8%)	0 (0)
Handgrip strength (HS)	6 (75%)	8 (34.8%)	0 (0)
Walking speed (SP)	5 (62.5%)	3 (13%)	0 (0)

In the following analysis, we compare four gait parameters obtained from the automated 6MWT system described in Chapter 2 with the three groups evaluated using the J-CHS method. The results are mainly interpreted using box plots, p-values, and d-values. The p-value is used to determine whether there is a statistically significant difference between two groups, while the d-value measures the size of the difference, also known as the effect size. A p-value less than 0.05 is considered statistically significant, and a larger d-value indicates a more noticeable difference between groups, suggesting stronger clinical or practical relevance.

Figure 3.2 shows boxplot distributions and p-values of four gait parameters across the three categories (frail, pre-frail, and non-frail) assessed by the J-CHS criteria. The box plots indicate that the distributions of step length (SL), gait velocity (GV), and six-minute walking distance (6MWD) all decrease as the level of frailty increases. This suggests that frail older adults tend to walk with shorter step lengths, slower gait speeds, and shorter walking distances. However, step cadence (SC) shows this decreasing trend only between the frail and non-frail groups. The p-values indicate that all four parameters show statistically significant differences between the frail and non-frail groups, as well as between the frail and pre-frail groups. However, between the pre-frail and non-frail groups, only SL and 6MWD show significant differences, while SC and GV do not. These results suggest that, among the four parameters, SL and 6MWD are more useful as simple indicators for the early identification of frailty in older adults.



(c) (d)

Figure 3.2 The box plots and p-value results show comparisons of gait parameters with the three groups of frailty in J-CHS as follows: (a) is SL, (b) is SC, (c) is GV, and (d) is 6MWD.

Table 3.3 provides detailed statistical analysis results of four gait parameters across the frail, pre-frail, and non-frail groups. The analysis of the effect size (d-value) shows that, although all parameters indicate significant differences between the frail and pre-frail groups, SC has the largest effect size ($p < 0.001$, $d = 1.712$). On the other hand, only SL and 6MWD show significant differences between the pre-frail and non-frail groups, with SL showing the largest effect size ($p = 0.015$, $d = 0.707$). These results suggest that gait parameters, especially SC, play an important role in identifying frailty, while SL is more useful in distinguishing the pre-frail stage.

Table 3.3 Results of the statistical analysis on five gait parameters for the groups classified by the J-CHS.

Parameter	Group	Mean ± SD	Pairwise 95% CI*	Group*	p-Value	d-Value
SL	Frail	0.52 ± 0.17	0.40 - 0.64	F and PF	0.026	0.964
	Pre-Frail	0.61 ± 0.07	0.58 - 0.64	PF and NF	*0.015*	*0.707*
	Non-Frail	0.67 ± 0.09	0.64 - 0.70			
SC	Frail	1.88 ± 0.09	1.82 - 1.94	F and PF	*< 0.001*	*1.712*
	Pre-Frail	2.15 ± 0.17	2.08 - 2.22	PF and NF	0.570	0.160
	Non-Frail	2.12 ± 0.11	2.08 - 2.16			
GV	Frail	0.97 ± 0.33	0.74 - 1.20	F and PF	< 0.001	1.509
	Pre-Frail	1.32 ± 0.19	1.24 - 1.40	PF and NF	0.059	0.538
	Non-Frail	1.43 ± 0.21	1.35 - 1.51			
6MWD	Frail	253 ± 118	172 - 335	F and PF	< 0.001	1.508
	Pre-Frail	385 ± 76	355 - 417	PF and NF	0.019	0.672
	Non-Frail	430 ± 60	409 - 453			

* Note: CI = confidence interval; F = Frail; PF = Pre-Frail; NF = Non-Frail.

3.3.2 Gait Parameters and J-CHS criteria

To gain a more comprehensive understanding of gait changes in older adults, we further analyzed the relationship between SL, SC, and the five scoring items of the J-CHS criteria, as shown in Table 3.4. In terms of average values, both SL and SC showed a decreasing trend when participants were judged as not meeting the criteria in any of the five items. The p-value results indicate that the differences in SL and SC between groups with and without unintentional weight loss were not significant ($p > 0.05$). However, both parameters showed significant differences in relation to whether the 5-meter walking speed was below 1.0 m/s ($p < 0.001$). In addition, SL showed significant differences in physical activity and grip strength items, while SC showed significant differences in the fatigue item. Since gait speed is determined by both SL and SC, it is expected that these parameters are highly related to the speed evaluation criterion. After removing the influence of the walking speed criterion, we found that SL and HS showed a significant relationship, with the largest effect size ($p < 0.001$, $d = 1.129$). Similarly, SC and EX showed a strong relationship with a large effect size ($p = 0.004$, $d = 0.952$).

Table 3.4. Correlation between five items of the J-CHS and parameters (SL and SC).

Parameter		SL			
		No*	Yes*	p-Value	d-Value
J-CHS	**WL**	0.63 ± 0.11	0.61 ± 0.11	0.512	0.238
	HS	0.65 ± 0.08	0.54 ± 0.13	<0.001	1.129
	EX	0.63 ± 0.11	0.61 ± 0.09	0.469	0.228
	SP	0.65 ± 0.08	0.47 ± 0.13	<0.001	1.725
	PA	0.65 ± 0.10	0.58 ± 0.12	0.037	0.610
Parameter		**SC**			
		No*	Yes*	p-Value	d-Value
J-CHS	**WL**	2.11 ± 0.15	2.03 ± 0.20	0.182	0.488
	HS	2.11 ± 0.14	2.07 ± 0.21	0.442	0.237
	EX	2.13 ± 0.14	1.99 ± 0.17	0.004	0.952
	SP	2.13 ± 0.14	1.91 ± 0.14	<0.001	1.406
	PA	2.11 ± 0.15	2.09 ± 0.18	0.666	0.125

* Note: No: the item is qualified; Yes: the item is not qualified.

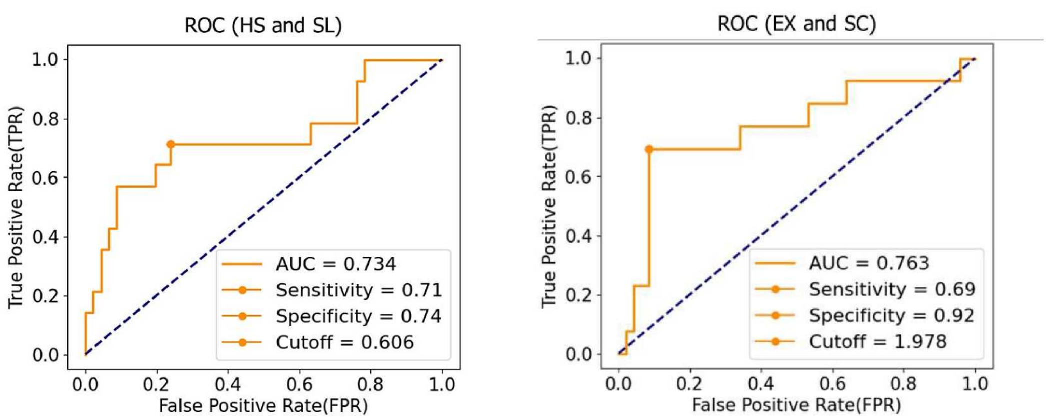
These findings highlight the importance of SL and SC in the J-CHS evaluation items and their value in reflecting physical frailty in older adults.

3.3.3 Calculation of SL and SC thresholds

In this chapter, our main goal is to determine a threshold for gait parameters to assess frailty. When dealing with uncertainty, binary classification models are often used by setting thresholds to divide samples into two categories, such as "positive" and "negative" or "1" and "0" [18]. This decision-making process helps explain the performance and outcomes of the model. Considering that the five items in the J-CHS evaluation also follow a binary scoring system using "1" and "0", we applied logistic regression model and ROC curve analysis to predict the cutoff values for SL and SC.

Based on the above p-value and d-value analysis, we used the criteria of HS and EX from the J-CHS to draw the ROC curves for SL and SC, as shown in Figure 3.3. In the ROC curve, the horizontal axis represents the false positive rate (FPR), and the vertical axis represents the true positive rate (TPR). Ideally, the closer the curve is to the upper-left corner, the better the model performance. The area under the ROC curve (AUC) is commonly used to evaluate classifier performance. The closer the AUC value is to 1, the better the model's ability to distinguish between the two classes. In general, when the AUC is greater than 0.7, the model is considered to have acceptable classification performance and reliable predictive power. When selecting thresholds using the ROC curve, the cutoff point is usually chosen at the position farthest from the diagonal line, which represents the threshold with the highest probability of correctly classifying positive and negative samples.

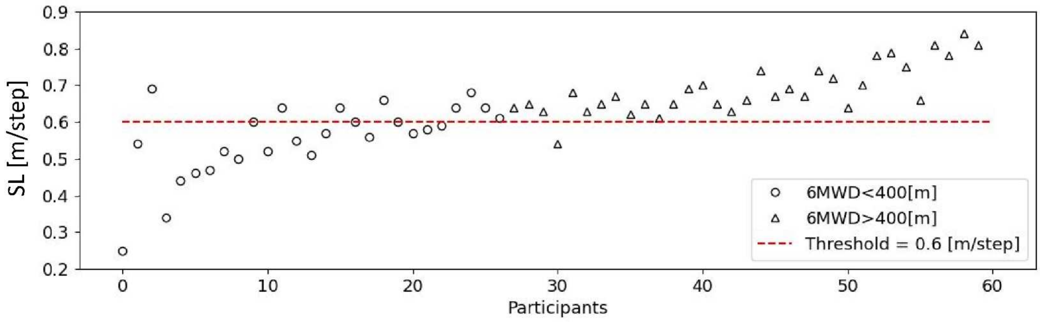
Figure 3.3(a) shows the ROC curve for SL based on the HS criterion. The AUC is 0.734, which is considered acceptable. The point farthest from the diagonal line on the ROC curve corresponds to the optimal classification threshold (cutoff = 0.606 [m/step], sensitivity = 0.71, specificity = 0.74). Figure 3.3(b) presents the ROC curve for SC based on the EX criterion, with an AUC of 0.763. The optimal threshold is 1.978 [steps/second], with a sensitivity of 0.69 and a specificity of 0.92. In the following analysis, the cutoff values for SL and SC are set at 0.6 [m/step] and 2.0 [steps/second], respectively.



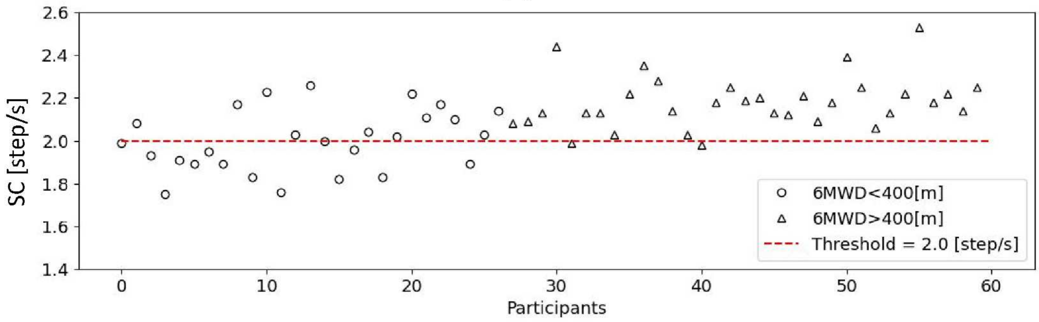
(a) **(b)**

Figure 3.3 Cutoff values of SL and SC. (a) ROC curve of SL vs HS (AUC is 0.734, the cutoff value is about 0.6 [m/step]); (b) ROC curve to SC vs EX (AUC is 0.763, the cutoff value is about 2.0 [step/s]).

Given that the 6MWD in the 6MWT is commonly used for clinical assessment, and 400m is often considered a critical point indicating good outdoor physical ability and a lower risk of cardiovascular disease, we further used 6MWD to validate the classification thresholds for SL and SC. Figure 3.4(a) shows the relationship between SL and 6MWD, where samples with 6MWD greater than 400m are marked with triangles, and those with less than 400m are marked with circles. The red line represents the SL threshold of 0.6 [m/step]. Figure 3.4(b) shows the relationship between SC and 6MWD, with the red line indicating the SC threshold of 2.0 [step/s]. The results showed that for samples with 6MWD over 400m, the classification accuracy was 97% for SL and 94% for SC, indicating that the defined thresholds are highly reliable.



(a)



(b)

Figure 3.4 Schematic diagram of 6MWD of 60 participants: (a) shows the distribution of SL, where the red line is the threshold 0.6 [m/step], triangular markers are for 6MWD>400 [m], and circular markers are for 6MWD<400 [m]; and (b) shows the distribution of SC, where the red line is the threshold 2.0 [step/s].

3.3.4 SC and SL distribution map

To objectively assess the physical frailty of elderly people due to the decline of muscle function, this study developed a gait distribution map using SC and SL as the core parameters to visualize individual gait characteristics.

Figure 3.5 shows a plot of the SC and SL distribution map to demonstrate the gait performance, where the horizontal axis represents SC and the vertical axis represents SL. The patients judged by the J-CHS criteria are described in different colors: frail in red, pre-frail in blue, and non-frail in green. The two dashed lines at SL = 0.6 [m/step] and SC = 2.0 [step/s] divide the map into four regions. Figure 3.6 further displays the distribution of older people in these three states in the distribution map. Almost non-frail and some pre-frail cases are distributed in Range I (SL > 0.6 [m/step], SC > 2.0 [step/s]), while almost frail cases are in Range III (SL ≤ 0.6 [m/step], SC ≤ 2.0 [step/s]). Range II (SL > 0.6 [m/step], SC ≤ 2.0 [step/s]) is a mixed region, and Range IV (SL ≤ 0.6 [m/step], SC > 2.0 [step/s]) shows mainly pre-frail with some of non-frail subjects.

Therefore, this study defines Range III as the physical frailty status due to weak gait performance, and Range I as the normal physical function status. Ranges II and IV are considered sub-health status, representing reduced performance in SC and SL, respectively, with Range IV regarded as having better gait performance than Range II.

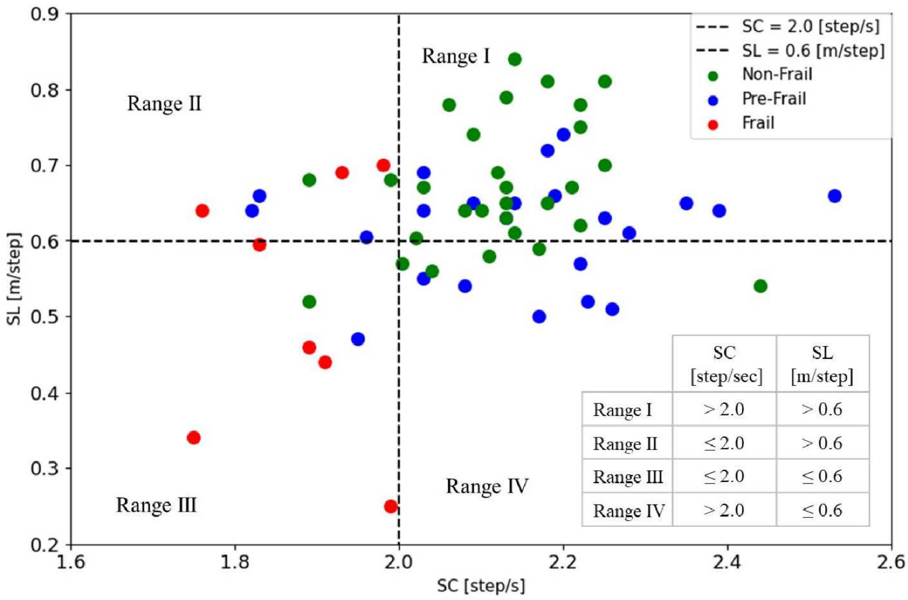
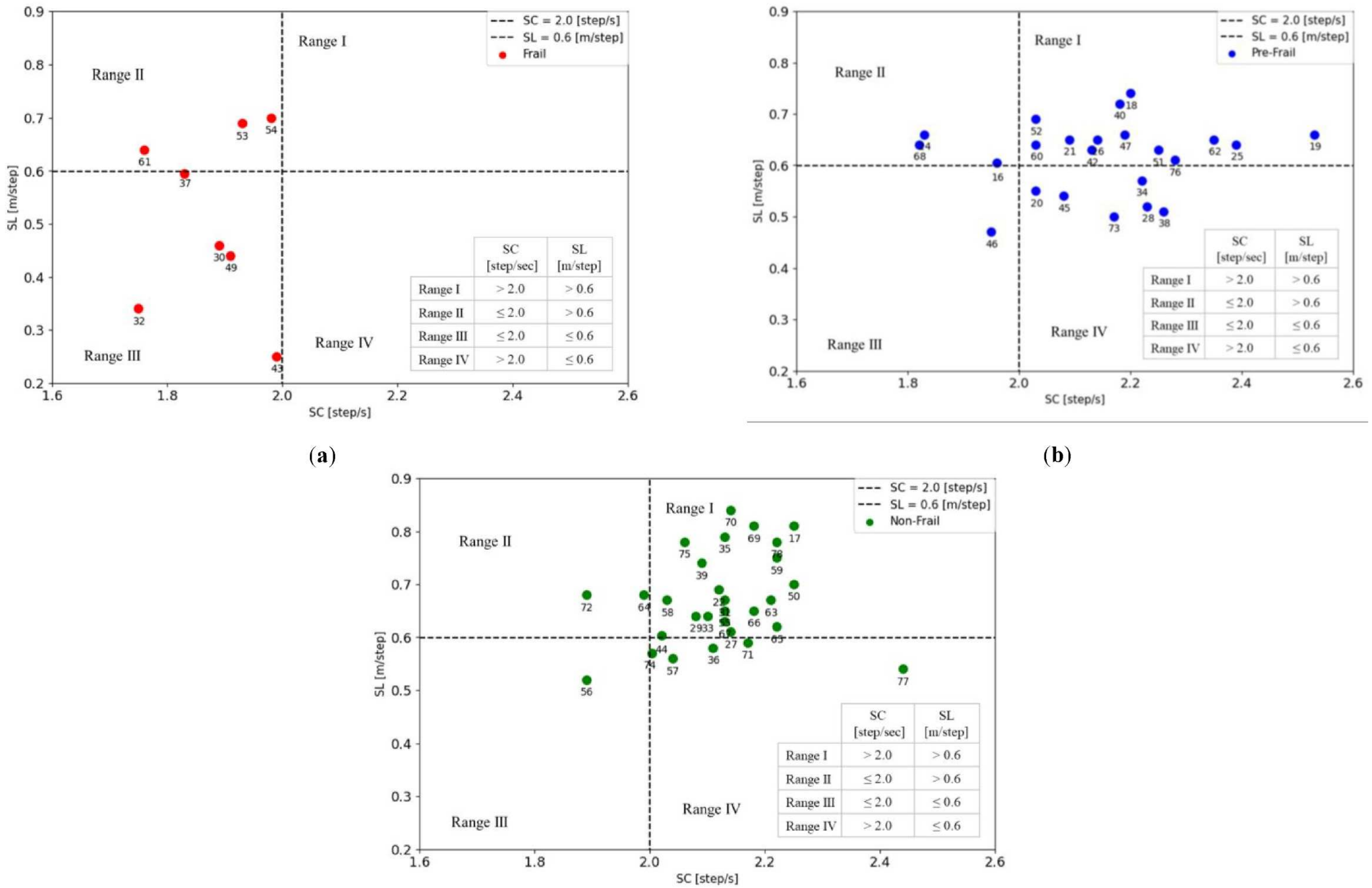


Figure 3.5 SC and SL distribution map. The dashed lines correspond to the threshold of 2.0 [step/s] for SC and 0.6 [m/step] for SL. The red markers are frail, the blue markers are pre-frail, and the green markers are non-frail, as assessed by the J-CHS criteria.



(c)

Figure 3.6 SC and SL distribution map: (a) shows the frail; (b) shows the pre-frail; and (c) shows the non-frail.

Figure 3.7 shows the percentage distribution of J-CHS assessment results across the four regions. A total of 62.5% of frail individuals were located in Range III, while the remaining 37.5% were in Range II. For the pre-frail and non-frail groups, the percentage increased gradually from weak to strong gait performance as defined by our criteria. 72.4% of non-frail individuals were in Range I, and 56.5% of pre-frail individuals were also found in Range I.

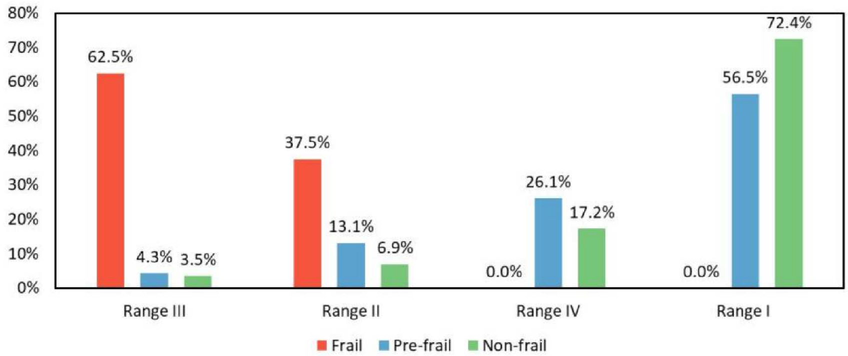


Figure 3.7 Percentages of the J-CHS assessment results in each of the four ranges.

Figure 3.8 shows the distribution of 23 participants who were classified as pre-frail according to the J-CHS assessment across the four gait performance regions. The results indicate that 13 participants were located in Range I, which represents the most normal gait status. Among them, the pre-frail classification of 10 participants was mainly influenced by questionnaire items, especially 7 individuals who were scored due to reporting "rarely participating in physical activity."

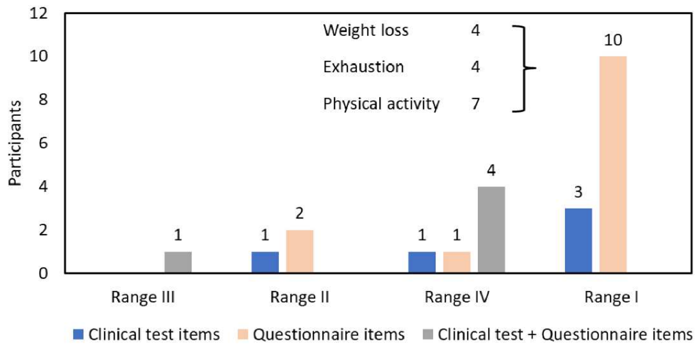


Figure 3.8 Distribution of pre-frail participants in the four ranges.

Figure 3.9 shows the distribution of 6MWD among the four regions of gait performance, with almost all of the 6MWD of individuals in Range I above 400m, and all below 330m in Range III.

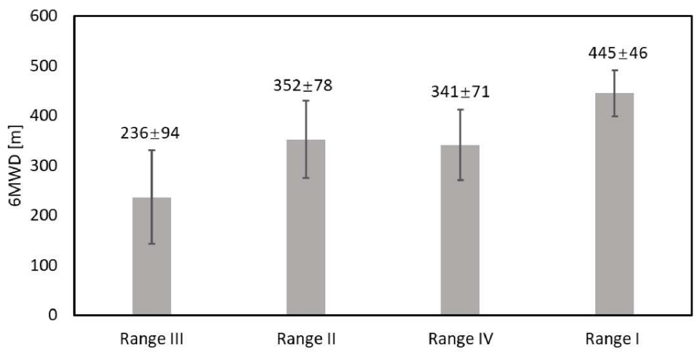


Figure 3.9 Distribution of 6MWD in four ranges.

3.4 Discussion

This chapter aims to propose an evaluation method based on gait parameters from the 6MWT to identify and visualize physical frailty caused by Lower limb muscle weakness. Comparing gait pattern with the J-CHS assessment criteria and combining statistical analysis with classification models, a practical and interpretable gait distribution map has been developed that provides a new approach for early detection of frailty and assessment of lower limb muscle function in elderly people.

Firstly, we categorised 60 older adults according to the J-CHS criteria. Table 3.2 shows that the mean age of the participants gradually increased as the severity of frailty increased, while handgrip strength and walking speed decreased. This further confirms the close relationship between frailty and declining muscle function. The proposed gait parameters in Table 3.3 showed high sensitivity for identifying frail and non-frail individuals, especially the frail status due to muscle weakness. The results suggest that SL and 6MWD, as independent parameters, show good ability in detecting frailty and can be used as valid indicators for initial screening. Also, SC and GV performed well in differentiating between frail and non-frail groups. However, it seems more difficult to effectively discriminate the patients in pre-frail by these gait parameters. This is because the pre-frail individuals assessed by the J-CHS criteria are affected not only by physical frailty but also by psychological and social frailty [14]. It is worth noting that while J-CHS is a widely used standard, it includes several highly subjective questionnaire items that may be affected by individual perception and self-awareness, potentially leading to under- or overestimation of frailty, particularly in pre-frail cases.

In general, the decline in GV of the elderly results is commonly regarded as a prominent feature of lower limb muscle failure and physical frailty [19]. Since GV is the coordinated result of SL and SC, we found that SL has a significant correlation with handgrip strength and SC has a correlation with exhaustion, as shown in Table 3.4. This finding aligns with our expectations that subjects with stronger upper limb handgrip strength also tended to have stronger lower limb strength [20, 21], enabling them to take larger strides. Furthermore, muscle fatigue or mental exhaustion may lead to a slowing of pace [22]. As assumed, these results suggest a close relationship between gait parameters and muscle function. SL may reflect muscle strength and extensibility associated with slow-twitch muscle fibers, while SC may be related to fast-twitch muscle fibers representing muscle fatigue.

Furthermore, we constructed ROC curves for SL and SC based on the HS and EX items from the J-CHS to evaluate their classification performance. The AUC values were 0.734 and 0.763, respectively, indicating that SL and SC can reliably distinguish physical status. The threshold values (SL = 0.6 [m/step], SC = 2.0 [step/s]) were not only statistically supported but also confirmed to be practically valid when compared with the clinical reference value of 6MWD (400 m), achieving classification accuracies of 97% and 94%.

The proposed SC-SL distribution map is shown in Figure 3.5, based on the threshold values mentioned above. Range I indicates the muscle strength in a normal state, while Range III represents much weaker muscle strength and easy fatigue. In Range III, both the fast-twitch and slow-twitch muscle fibers may be at their weakest state. Range II and Range IV could be considered the slow-twitch and fast-twitch muscle fibers in a normal state, respectively, while the fast-twitch and slow-twitch muscle fibers may be in a sub-normal state.

In the current muscle impedance training, fast muscle fibers tend to be activated and developed through high-intensity and explosive exercises such as weightlifting and jumping, while slow muscle fibers are targeted for increased fiber thickness with light-load or low-intensity repetitive movements, such as walking and jogging [23]. For the elderly, the exercise of fast-twitch muscles is risky and impractical, so they may maintain and improve slow-twitch muscle fibers through low-intensity activities. This implies that patients in Range IV may recover to their normal state through physical activity, whereas those in Range II may only maintain their current state or delay the decline to the Range III muscle state through appropriate intensity activity. Additionally, we also found that the average age of the four ranges gradually increases with the decline in muscle status (Range I: 68.91 ± 6.79; Range IV: 73.00 ± 6.88; Range II: 75.10 ± 6.66; Range III: 76.67 ± 5.87). This also means that muscle decline is a common phenomenon among older people.

We compared the results of the J-CHS assessment in these four regions. The results in Figure 3.7 show that 62.5% of frail patients were in Range III and 37.5% in Range II, while 72.4% of the non-frail patients were in Range I and 17.2% in Range IV. These results suggest that the pre-frail and non-frail patients in Range II may develop sarcopenic frailty and that the pre-frail individuals in Range IV could return to a non-frail condition through appropriate intensity activity.

In addition, we found that about 56.5% of pre-frail cases were in Range I, who did not have a problem in the physical aspect. This fact might be subjectively influenced by the J-CHS questionnaire, such as lack of physical activity, rather than true muscle weakness. Since this study was conducted during the COVID-19 pandemic, more than half of the pre-frail patients in Range I refrained from going out, which supports the validity of our results.

In summary, the SC-SL distribution map provides a practical and effective tool for a quick view of frail conditions in older people, especially in identifying physical frailty caused by declining muscle function. This tool may enhance clinical assessment and aid in developing targeted interventions. For example, psychological guidance and regular physical activity may help patients in Range IV recover to a healthy state. Although the underlying mechanisms of frailty and 6MWT are not yet fully understood, significant correlations were found between the gait parameters, such as step length, step cadence, and gait speed, extracted from the walking data and the indicators in the J-CHS criteria, including handgrip strength, exhaustion, and walking speed. Especially, step cadence was correlated with exhaustion in the J-CHS, which explains the fact that the exhaustion actually diagnosed in the J-CHS is mainly physical aspects. Additionally, Table 3.4 shows that there is a difference between step length and the physical activity indicator in the J-CHS criteria with a p-value of 0.037, suggesting that our proposed method closely resembles the J-CHS criteria (4 out of 5 items are related) in theoretically. These findings suggest that our proposed method is more objective and valuable than the J-CHS criterion in describing the physical frailty caused by the lower limb muscle weakness of older adults.

3.5 Conclusion

This study proposed a new gait analysis method based on the 6MWT, using two key parameters, SL and SC, to construct a gait distribution map for identifying and visualizing physical frailty caused by lower limb muscle weakness. Clinical data from 60 older participants showed that SL and SC effectively reflected differences in walking ability and correlated strongly with HS and EX, two important items in the J-CHS frailty criteria, indicating great potential for frailty detection and clinical interpretation. Statistical testing and ROC curve analysis confirmed SL = 0.6 [m/step] and SC = 2.0 [step/s] as key thresholds for evaluating muscle capacity. Participants were categorised into four gait performance regions based on these thresholds, clearly demonstrating differences in muscle condition. Compared with the semi-subjective J-CHS approach, which relies on questionnaires, this method provides a more objective evaluation of frailty, allowing for earlier and more accurate identification of at-risk individuals. Furthermore, the proposed SC-SL distribution map can be used to assess muscle status in older adults and guide personalized exercise interventions and rehabilitation strategies. Overall, this method offers strong potential for clinical application and may contribute to more objective, convenient, and effective healthcare solutions for the aging population.

References

[1] Kojima G, Iliffe S, Taniguchi Y, et al. Prevalence of frailty in Japan: a systematic review and meta-analysis[J]. Journal of epidemiology, 2017, 27(8): 347-353.111

[2] Richards S J G, Frizelle F A, Geddes J A, et al. Frailty in surgical patients[J]. International journal of colorectal disease, 2018, 33: 1657-1666.

[3] Topinková E. Aging, disability and frailty[J]. Annals of nutrition & metabolism, 2008, 52: 6-11.

[4] Perazza L R, Brown-Borg H M, Thompson L D V. Physiological systems in promoting frailty[J]. Comprehensive Physiology, 2022, 12(3): 3575-3620.

[5] Kuh D. A life course approach to healthy aging, frailty, and capability[J]. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 2007, 62(7): 717-721.

[6] Life expectancy and healthy life expectancy: https://www.who.int/data/gho/data/themes/mortamort-and-global-health-estimates/ghe-life-expectancy-and-healthy-life-expectancy (accessed on8 April 2025).

[7] Choi M, Sempungu J K, Lee E H, et al. Living longer but in poor health: healthcare system responses to ageing populations in industrialised countries based on the Findings from the Global Burden of Disease Study 2019[J]. BMC Public Health, 2024, 24(1): 576.

[8] Fried L P, Tangen C M, Walston J, et al. Frailty in older adults: evidence for a phenotype[J]. The journals of gerontology series a: biological sciences and medical sciences, 2001, 56(3): M146-M157.

[9] Satake S, Arai H. The revised Japanese version of the Cardiovascular Health Study criteria (revised J-CHS criteria)[J]. Geriatrics & gerontology international, 2020, 20(10).

[10] Chen L K, Woo J, Assantachai P, et al. Asian Working Group for Sarcopenia: 2019 consensus update on sarcopenia diagnosis and treatment[J]. Journal of the American Medical Directors Association, 2020, 21(3): 300-307. e2.

[11] Hernández Morante J J, Gómez Martínez C, Morillas-Ruiz J M. Dietary factors associated with frailty in old adults: a review of nutritional interventions to prevent frailty development[J]. Nutrients, 2019, 11(1): 102.

[12] Lorbergs A L, Prorok J C, Holroyd-Leduc J, et al. Nutrition and physical activity clinical practice guidelines for older adults living with frailty[J]. The Journal of frailty & aging, 2022, 11(1): 3-11.

[13] Fiatarone M A, O'Neill E F, Ryan N D, et al. Exercise training and nutritional supplementation for physical frailty in very elderly people[J]. New England Journal of Medicine, 1994, 330(25): 1769-1775.

[14] Pilotto A, Custodero C, Maggi S, et al. A multidimensional approach to frailty in older people[J]. Ageing research reviews, 2020, 60: 101047.

[15] Ikezoe T, Nakamura M, Shima H, et al. Association between walking ability and trunk and lower-limb muscle atrophy in institutionalized elderly women: a longitudinal pilot study[J]. Journal of physiological anthropology, 2015, 34: 1-6.

[16] ATS. Committee on Proficiency Standards for Clinical Pulmonary Function Laboratories, ATS Statement[J]. American Journal of Respiratory and Critical Care Medicine, 2002, 166(1): 111-117.

[17] Enright P L. The six-minute walk test[J]. Respiratory care, 2003, 48(8): 783-785.

[18] Kiang M Y. A comparative assessment of classification methods[J]. Decision support systems, 2003, 35(4): 441-454.

[19] Batista F S, Gomes G A O, Neri A L, et al. Relationship between lower-limb muscle strength and frailty among elderly people[J]. Sao Paulo Medical Journal, 2012, 130: 102-108.

[20] Leong D P, Teo K K, Rangarajan S, et al. Prognostic value of grip strength: findings from the Prospective Urban Rural Epidemiology (PURE) study[J]. The lancet, 2015, 386(9990): 266-273.

[21] Chan J, Lu Y C, Yao M M S, et al. Correlation between hand grip strength and regional muscle mass in older Asian adults: an observational study[J]. BMC geriatrics, 2022, 22(1): 206.

[22] Ament W, Verkerke G J. Exercise and fatigue[J]. Sports medicine, 2009, 39: 389-422.

[23] Wilson J M, Loenneke J P, Jo E, et al. The effects of endurance, strength, and power training on muscle fiber type shifting[J]. The Journal of Strength & Conditioning Research, 2012, 26(6): 1724-1729.

Chapter 4 Quantification of lower limb muscle weakness, sarcopenia, and frailty

4.1 Overview

Sarcopenia is a common disease with loss of muscle capacity among older adults that significantly affects their quality of life [1, 2]. Its main feature is the progressive loss of muscle mass and muscle function. According to the latest consensus from the Asian Working Group for Sarcopenia (AWGS), sarcopenia is defined as "age-related loss of muscle mass, accompanied by decreased muscle strength and/or reduced physical performance" [3]. This consensus highlights the age-related nature of sarcopenia and points out that it may begin to develop earlier in life.

Figure 4.1 shows that the AWGS has proposed specific assessment criteria for Asian populations, which include three phenotypes: (1) muscle strength, (2) physical performance, and (3) muscle mass.

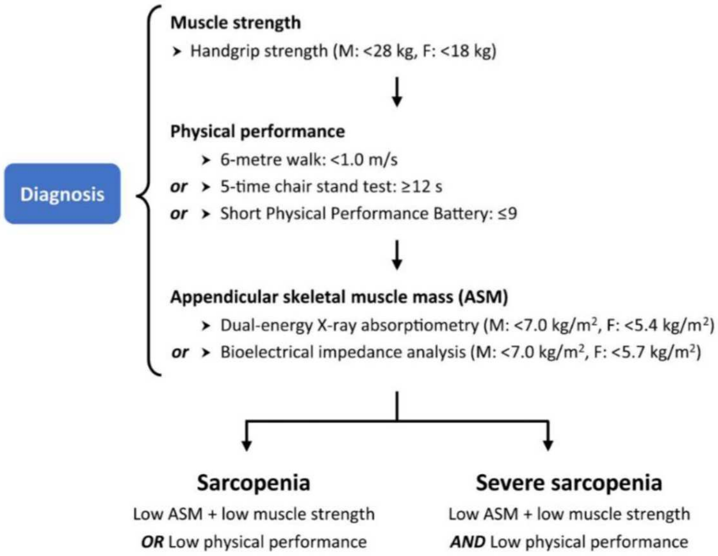


Figure 4.1 Sarcopenia diagnosis using AWGS criteria.

(1) Muscle strength is commonly assessed using a handgrip test. The method involves measuring the average handgrip strength (HS) of the left and right hands using dynamometer, usually taking 2 to 3 trials and recording the highest value. According to the AWGS guidelines [3], low muscle strength is defined as HS less than 28 kg for men and less than 18 kg for women. HS not only reflects muscle strength but is also considered an important indicator for predicting functional decline and adverse health outcomes in older people.

(2) Physical performance is commonly assessed by the walking speed test, the Five Times Sit to Stand Test (SS-5), and the Short Physical Performance Battery (SPPB). The speed test usually measures normal walking speed (WS) over a distance of 5m or 6m, and a WS of less than 1.0 m/s is considered low physical performance [3, 4]. The SS-5 evaluates the time it takes for a person to stand up and sit down five times; if it takes more than 12 seconds [3, 5], it indicates a decline in function. An SPPB score below 9 points suggests limited physical function [3, 6], meaning the elderly may already experience difficulty in daily activities, such as slow walking, poor balance, or trouble standing up.

(3) Muscle mass is usually assessed using dual-energy X-ray absorptiometry (DXA) or bioelectrical impedance analysis (BIA). The evaluation index is the Appendicular Skeletal Muscle Index (ASMI), which is calculated by dividing the appendicular skeletal muscle mass by the square of height. According to the AWGS 2019 guidelines in BIA, low muscle mass is defined as ASMI below 7.0 kg/m² for men and below 5.7 kg/m² for women [3].

This comprehensive evaluation method reflects a deeper understanding of sarcopenia. It not only focuses on the loss of muscle mass but also emphasizes the combined decline in strength and performance. Notably, in the updated consensus, low muscle mass is considered a prerequisite for diagnosis. When it is accompanied by either reduced muscle strength or physical performance, it is classified as sarcopenia. If both strength and performance are reduced, it is diagnosed as severe sarcopenia. In addition, if only muscle strength and/or physical performance decline is observed, it is considered possible sarcopenia.

Sarcopenia is one of the common health problems among older adults. It is not only characterized by a decline in muscle function, but also closely linked to various negative health outcomes. The most direct impact is the reduction in the ability to perform daily activities, such as walking, standing up, or climbing stairs [7]. In severe cases, it may lead to loss of independence and increase the risk of falls and fractures, which raises the likelihood of disability [7]. In addition, sarcopenia often coexists with chronic conditions such as diabetes, cardiovascular disease, and chronic obstructive pulmonary disease (COPD) [8, 9]. The possible underlying mechanisms include chronic inflammation, insulin resistance, and metabolic disorders. On a psychological and social level, sarcopenia may lead to reduced social interaction and emotional problems, increasing the risk of loneliness and depression. It is also associated with higher hospitalization rates and longer hospital stays [10], resulting in greater use of medical resources and heavier caregiving burdens. These factors can reduce the quality of life for patients and challenge the stability of the healthcare system.

One of the other things that correlates with quality of life and even healthy life expectancy in the elderly is frailty [11]. It has been reported that more than half of frail individuals are diagnosed with sarcopenia [12]. Although frailty and sarcopenia differ in their manifestations and diagnostic criteria, they are closely related. Sarcopenia further exacerbates the frail condition through the reduction of muscle mass and strength, while the presence of frailty accelerates muscle decline, creating a vicious cycle [13]. Therefore, early identification and intervention in the severity of sarcopenia and frailty are important for slowing physical performance decline and improving the quality of life for the elderly.

About the decline in muscle strength and performance in elderly people, there is strong evidence that muscle function can be improved through exercise [14]. Appropriate physical activity interventions can significantly enhance physical performance, helping delay or even reverse the progression of muscle decline [15], thus providing a practical approach and basis for prevention and treatment. However, despite the significant benefits of physical activity for improving the health of older adults, an important problem in practice is the lack of effective metrics to assess the interventions and rehabilitation effects when using physical activity. Although the AWGS and J-CHS criteria are widely used for assessing sarcopenia and frailty, these criteria provide qualitative descriptions of the disease, lacking objective and quantitative indicators to evaluate the severity of the disease and the effectiveness of interventions. In particular, during interventions for frailty and sarcopenia, it is often difficult to accurately measure the improvement in an individual's health from physical activity, which limits the optimization of intervention programs and the development of personalized treatment strategies.

The Six-Minute Walk Test (6MWT) has shown great utility as a simple, non-invasive, and easy-to-administer method in assessing the physical performance of older people. Clinical studies have found that older adults with sarcopenia walk a significantly shorter distance during the 6MWT compared to healthy individuals [16]. The underlying reasons include weakened lower-limb muscle contraction strength, reduced exercise endurance, and lack of movement coordination. The 6MWT does more than just measure whether a person can walk; it also evaluates how far they can walk, whether they can maintain continuous walking, and the stability of their gait. These indicators closely reflect physical performance in daily life, making 6MWT an effective tool for assessing lower limb muscle capacity and overall physical health in older adults.

Additionally, the 6MWT, as a time-restricted walking test, effectively evaluates an individual's exercise endurance. This test reflects the physical function and endurance levels of elderly individuals or patients by recording the walking distance over a six minutes. Individuals with higher exercise endurance are generally able to maintain a higher walking speed during the test, experience less fatigue, and sustain stable cardiopulmonary function. The efficient coordination of their muscular and cardiopulmonary systems allows them to sustain longer periods of efficient walking within the same time, resulting in increased walking distance along with a corresponding increase in energy expenditure. On the other hand, this also illustrates that energy expenditure is an important indicator of muscle strength, as it directly reflects the amount of work required by muscles during physical activity [17]. The stronger the muscle strength, the more efficiently muscles can perform tasks, leading to increased energy expenditure per unit of time [18]. Therefore, when assessing the degree of disease improvement or rehabilitation outcomes, the six-minute walking energy expenditure (6MWEE) data provides healthcare with invaluable information that can help doctors better identify patients with limited muscle function and, based on their performance, develop more personalized and effective rehabilitation plans.

The main objective of this chapter is to explore how walking data can be used to quantify lower limb muscle strength and further assess the severity of frailty diagnosed by the J-CHS criteria and sarcopenia diagnosed by the AWGS criteria, as well as the effects of clinical improvements. This study first analyses the relationship between 6MWT data with 6MWEE, and combines gait parameters such as step length (SL) and step cadence (SC) to propose a new evaluation metric, the Walking Muscle Strength (WMS) index, to quantitatively assess changes in lower limb muscle strength. Additionally, this chapter compares the WMS index with the diagnostic results from J-CHS and AWGS criterias to validate its effectiveness and practicality, aiming to establish a comprehensive muscle quantification indicator, which can more accurately identify muscle weakness in walking performance and provide more reliable data support for the early screening and intervention of sarcopenia or frailty.

4.2 Methods

4.2.1 Participants

Consistent with the description in Chapter 2, we recruited 60 elderly participants from the university-affiliated hospital as the sample data.

4.2.2 Experimental process

(1) After signing the informed consent form, participants provided relevant information (such as gender, age, weight, and height) through a brief interview.

(2) We determine whether the participants have possible sarcopenia based on the HS and/or WS items in the AWGS criteria.

(3) For suspected cases of sarcopenia, we performed ASMI tests using the InBody S10 analyser (InBody Co., Ltd., Korea, as shown in Figure 4.2 [19]) and assessed for sarcopenia according to the AWGS method (Figure 4.1).

Figure 4.2 Schematic of ASMI testing with the InBody S10 analyser.

(4) Consistent with the description in Chapter 3, the 6MWT was administered to 60 participants and frailty was diagnosed using the J-CHS criteria.

4.2.3 Gait parameters

In this chapter, we not only used the four gait parameters introduced in Chapter 2 (SL, SC, GV, and 6MWD), but also calculated the energy expenditure of participants during the 6MWT.

In the 6MWT, the amount of energy expended can be an important reference for assessing muscle function. Individuals with decreased muscle function usually show shorter walking distances and slower speeds, leading to significantly lower energy consumption. This low energy use reflects a decline in muscle metabolism and physical performance, indirectly indicating reduced muscle endurance and function [20]. Therefore, combining gait parameters with calorie consumption helps in identifying declines in muscle strength and physical performance.

6MWEE [kcal/h] represents the total energy expenditure of walking activity [21, 22], which can be calculated by Equation (4.1). This calculation involves the individual's Basal Metabolic Rate (BMR), the Metabolic Equivalent of Task (MET), and the duration of the activity (Time).

$$6MWEE = BMR * MET * Time \tag{4.1}$$

BMR is the number of calories the body needs to perform basic life-sustaining functions [22]. The most widely used prediction equation for estimating BMR is the Harris-Benedict Equation (HBE) [23], which was developed in 1918, as shown in Equation (4.2). The HBE takes into account factors such as age (A), gender (G), weight (W: kg), and height (H: cm) to estimate the number of calories expended by an individual at rest.

$$\begin{cases} Male: BMR = 66.4730 + 13.7516 * W + 5.0033 * H - 6.7550 * A \\ Female: BMR = 655.0955 + 9.5634 * W + 1.8496 * H - 4.6756 * A \end{cases} \tag{4.2}$$

MET is a unit used to estimate the amount of oxygen consumed and the number of calories burned during physical activity [24]. It represents the ratio of the metabolic rate during a specific physical activity to the resting metabolic rate, where a higher MET value indicates greater activity intensity. We calculated the MET of walking using the method proposed by Brooks et al., as Equation (4.3) [24].

$$MET = 0.832 * GV - 0.016 * W - 0.196 * G + 1.034 \tag{4.3}$$

Where GV is the velocity calculated by Equation (2.5), W is the body weight [Kg], and G is the gender (1: male, 2: female).

4.2.3 Statistical analysis

The statistical methods are consistent with those described in Chapter 3. We used the Shapiro–Wilk test to check whether the variables obeyed the normal distribution. The Student's t-test was used for the two groups' data that conformed to a normal distribution, and the ANOVA analysis was used for the data that did not conform to a normal distribution. We compared differences in the gait parameters among clinical diagnostic results and calculated the p-values and d-values to determine the significance and Cohen's d effect size of these differences. In addition, for some statistical tests, the mean value and standard deviation were reported, p-values less than 0.05 were considered to be statistically significant, and d-values = 0.2, 0.5, and 0.8 were considered small, medium, and large effects.

4.3 Results

4.3.1 Participants and sarcopenia evaluation

This study recruited 60 older adults and collected their basic personal information. They were classified according to the AWGS criteria as shown in Table 4.1, and 10 of them were identified as having sarcopenia.

Table 4.1 Participant demographic characteristics and sarcopenia assessment in theAWGS.

Characteristic	Sarcopenia		p-Value	d-Value
	Yes, n=10	No, n=50		
Male,(Female)	9 (1)	37 (13)	---	---
Age, mean ± sd	77.80 ± 4.80	70.3 ± 7.24	<0.001	1.084
Height, cm, mean ± sd	158.11 ± 6.54	164.29 ± 7.60	0.019	0.830
Weight, kg, mean ± sd	50.37±6.17	66.02±11.07	<0.001	1.496
Body mass index, kg/m2, mean ± sd	20.12±1.92	24.48±3.98	<0.001	1.167
Average handgrip strength, kg, mean ± sd	23.04±5.50	30.76±7.45	0.002	1.075
5 m walking speed, m/sec, mean ± sd	0.96±0.26	1.32±0.21	0.001	1.648
Observed 6MWT Parameters				
SL, m/step, mean ± sd	0.51±0.15	0.65±0.08	0.016	1.484
SC, step/sec, mean ± sd	1.97±0.16	2.13±0.15	0.013	1.055
GV, m/sec, mean ± sd	1.01±0.3	1.39±021	0.003	1.679
6MWD, m , mean ± sd	274.3±113.46	412.48±71.22	0.004	1.743
6MWEE, kcal/h, mean ± sd	11.75±4.89	20.95±4.52	<0.001	2.009

A comparison between the two groups showed that all physical characteristics and 6MWT gait parameters in the sarcopenia group were lower than those in the non-sarcopenia group, with statistically significant differences and large effect sizes. This highlights that gait parameters can serve as effective indicators for evaluating muscle function status in clinical practice.

Table 4.2 Sarcopenia and frailty assessment in the 10 participants.

No	M/F	AWGS-2019				J-CHS
		Muscle strength (GS)	Physical performance (GV)	Muscle mass (AMSI)	Diagnosis	
No.30	M	22.7	0.88	6.6	Severe sarcopenia	Frail
No.32	M	18.8	0.62	6.5	Severe sarcopenia	Frail
No.43	M	22.85	0.5	5.1	Severe sarcopenia	Frail
No.73	M	25.85	0.92	5.5	Severe sarcopenia	Prefrail
No.38	M	20.95	1.04	6.1	Sarcopenia	Prefrail
No.44	M	27.5	1.12	6.4	Sarcopenia	Prefrail
No.49	M	31.5	0.92	5.3	Sarcopenia	Frail
No.53	M	17.35	1.31	6.6	Sarcopenia	Frail
No.61	M	28.95	0.95	6.8	Sarcopenia	Frail
No.54	F	13.95	1.31	4.7	Sarcopenia	Frail

Table 4.2 summarizes the basic information of participants diagnosed with sarcopenia, including muscle strength, physical performance, and muscle mass, along with their frailty status based on the J-CHS assessment. The results showed that 4 participants were diagnosed with severe sarcopenia, and 6 with sarcopenia. Most of them were also assessed as frail, while a few were in the pre-frail state. These findings further support the point made in Chapter 3 that frailty largely reflects a decline in muscle function.

4.3.2 Calculate walking muscle strength (WMS)

The results of Table 4.1 and Table 4.2 show that individuals with poor gait performance in the 6MWT tend to have higher rates of sarcopenia and frailty. This suggests that low gait patterns are a key indicator of muscle weakness in older adults. In Chapter 3, we discussed how the gait parameters SL and SC can serve as alternatives to walking speed and are closely related to muscle status. SL may reflect muscle strength and extensibility associated with slow-twitch muscle fibers, while SC may be related to fast-twitch muscle fibers representing muscle fatigue. In Table 4.1, the p-value and effect size (d-value) show that 6MWEE has a significant difference and the largest effect size ($p < 0.001$, $d = 2.009$), indicating its strong association with sarcopenia status. 6MWEE is the energy expenditure [kcal/h] during the 6MWT, which is calculated from the MET for evaluating the level of physical activity in the elderly [25]. Doctors typically develop different exercise programs based on the value of MET to improve the health status and quality of life for older people.

Additionally, given that the 6MWT is an effective method for assessing an individual's exercise endurance, participants with stronger endurance and muscle ability tend to experience less fatigue and walk greater distances within the six minutes, as well as have higher energy expenditure in terms of a combination of cardiorespiratory and gait characteristics. This also suggests that SC, which is associated with reduced fatigue, SL, which correlates with longer walking distances, and 6MWEE, reflecting muscle work efficiency, are all effective indicators for evaluating exercise endurance. Therefore, the main goal of this chapter is to propose a quantitative indicator of walking muscle strength using gait parameters (SL, SC, and 6MWEE).

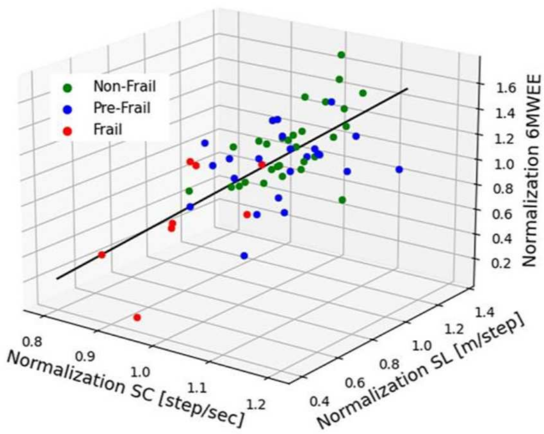
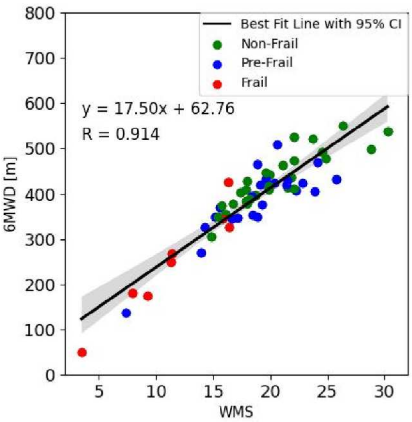


Figure 4.3 Three-dimensional scatter plot of SC, SL, and 6MWEE. The linear fit demonstrates the strong correlation ($r = 0.853$).

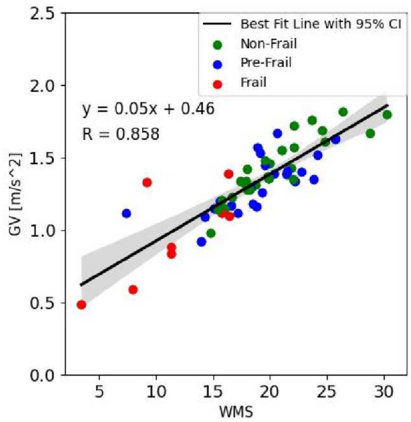
Figure 4.3 shows a three-dimensional scatter plot of SL, SC, and 6MWEE, where each parameter was normalized by its average value. A strong correlation is demonstrated through linear fitting (r = 0.853). Based on this, a new variable, Walking Muscle Strength (WMS) index, is defined as a multivariable function of SL, SC, and 6MWEE to assess muscle strength. The WMS index for each subject is represented by the projection length onto the fitted line, and its calculation method is derived through multiple regression analysis, as shown in equation (4.4).

$$WMS = 0.064 * SL + 0.189 * SC + 0.859 * 6MWEE + 1.554 \tag{4.4}$$

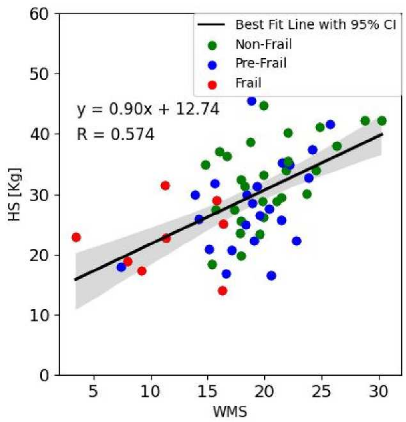
To validate the effectiveness of the WMS values derived from the fitting Equation (4.4), a correlational analysis between the WMS index and other physiological indicators was conducted. The results are shown in Figure 4.4. According to clinical test guidelines, the 6MWD is an important parameter of the 6MWT, and Figure 4.4 (a) shows a strong correlation (r = 0.914) between the 6MWD with WMS. Additionally, GV and HS have been identified as indicators of muscle strength. Figures 4.4 (b) and (c) show that WMS is strongly (r=0.858) and moderately (r=0.574) correlated with GV and HS, respectively. These results confirm the potential value of the WMS Index in assessing muscular strength and endurance.



(a)



(b)



(c)

Figure 4.4 Correlations between the WMS index with physiological indicators: (a) 6MWD (r = 0.914), (b) GV (r = 0.858), and (c) HS (r = 0.574).

4.3.3 Scoring of walking muscle strength (WMS)

To evaluate the physical walking performance using a simple scale, we normalized the WMS using the sigmoid function as given by Equation (4.5). Here, the parameters a and b were used to control the shape of the sigmoid function. In many medical studies and clinical evaluations, a 6MWD greater than 400 m was usually considered normal, reflecting good walking ability and a lower risk of cardiovascular disease [26]. The threshold of 400 m was used to label the WMS (6MWD $\geq$ 400 [m] as 1, and 6MWD < 400 [m] as 0), and the optimal parameters were obtained as a = 1.198 and b = 18.388 by the least squares method.

$$S(WMS) = \frac{1}{1 + e^{-a*(WMS-b)}} \tag{4.5}$$

Figure 4.5 shows the plot of WMS as a sigmoid function in the range between 0 and 1. Here, we defined a scale of WMS for scoring the walking muscle strength by WMS1 (<0.01), WMS2 (0.01~0.50), WMS3 (0.50~0.95), and WMS4 (>0.95).

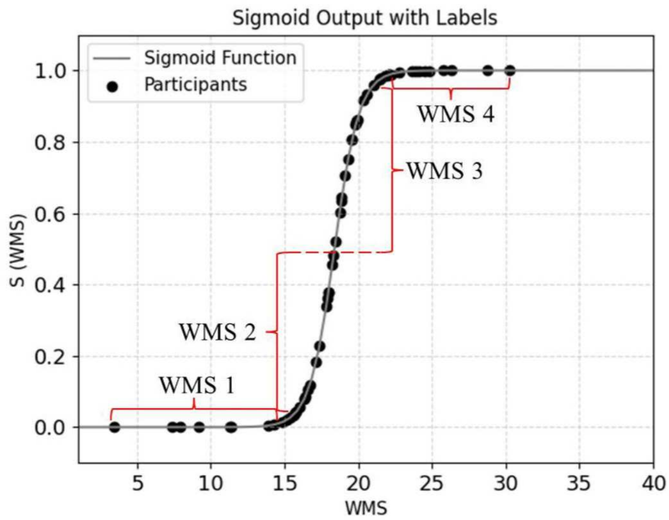


Figure 4.5 The WMS index of the participants was divided into four levels using the sigmoid function: WMS 1 (<0.01), WMS 2 (0.01~0.50), WMS 3 (0.50~0.95), and WMS 4 (>0.95).

The thresholds of 0.01 and 0.95 were chosen because when a participant's S(WMS) is below 0.01, their 6MWD is typically less than 300 meters, while when S(WMS) is above 0.95, their 6MWD is generally greater than 400 meters. The total distances at 300 and 400 meters are usually regarded as key thresholds, where a 6MWD above 400 meters tends to indicate good cardiorespiratory function and Physical activity ability outside the home [26], while below 300 meters may be at higher risk of disease and mortality for older adults [27].

4.3.4 WMS score with gait distribution map and sarcopenia

This study used a gait distribution map with SC and SL as core parameters to visualize individual gait patterns and objectively demonstrate the status of lower limb muscle weakness in older adults.

Figure 4.6 shows the SC-SL distribution map of different gait performances, where the horizontal axis represents SC and the vertical axis represents SL. Four WMS scores are shown in different colors: WMS1 in red, WMS2 in blue, WMS3 in pink, and WMS4 in green. Squares represent participants with sarcopenia, and triangles represent those with severe sarcopenia. Two dashed lines at SL = 0.6 [m/step] and SC = 2.0 [step/s] divide the plot into four ranges. Figure 4.7 further illustrates the distribution of the four WMS groups. Most WMS1 cases are located in Range III (SL ≤ 0.6 [m/step], SC ≤ 2.0 [step/s]), while all WMS4 cases are in Range I (SL > 0.6 [m/step], SC > 2.0 [step/s]). Notably, there are almost no sarcopenia cases in Range I.

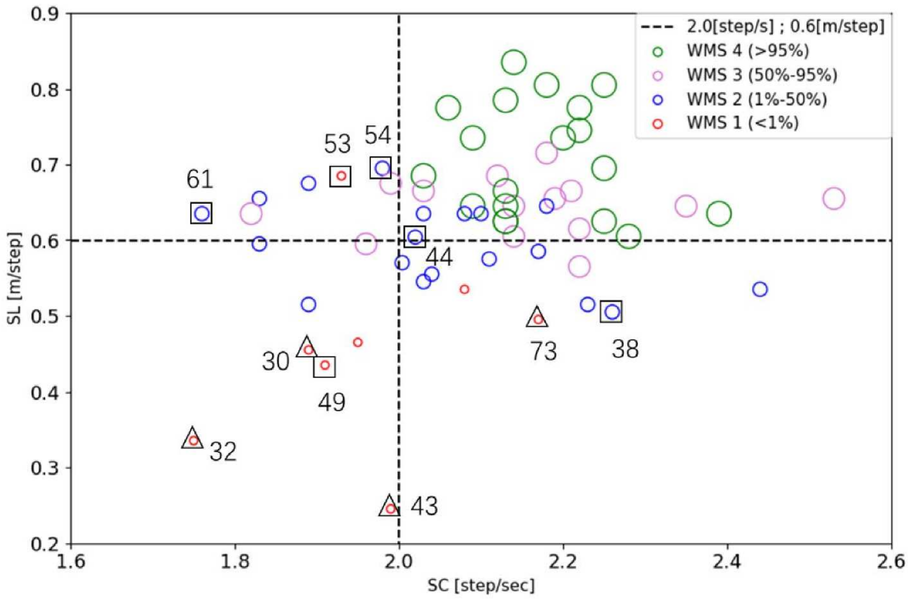


Figure 4.6 SC-SL distribution map. The dashed lines correspond to the threshold of 2.0 [step/s] for SC and 0.6 [m/step] for SL. The red markers are WMS1, the blue markers are WMS2, the pink markers are WMS3, and the green markers are WMS4. The square markers are sarcopenia (□: Low muscle strength/physical performance + muscle mass), and the triangle markers are severe sarcopenia (△: Low muscle strength + physical performance + muscle mass), as assessed by the AWGS.

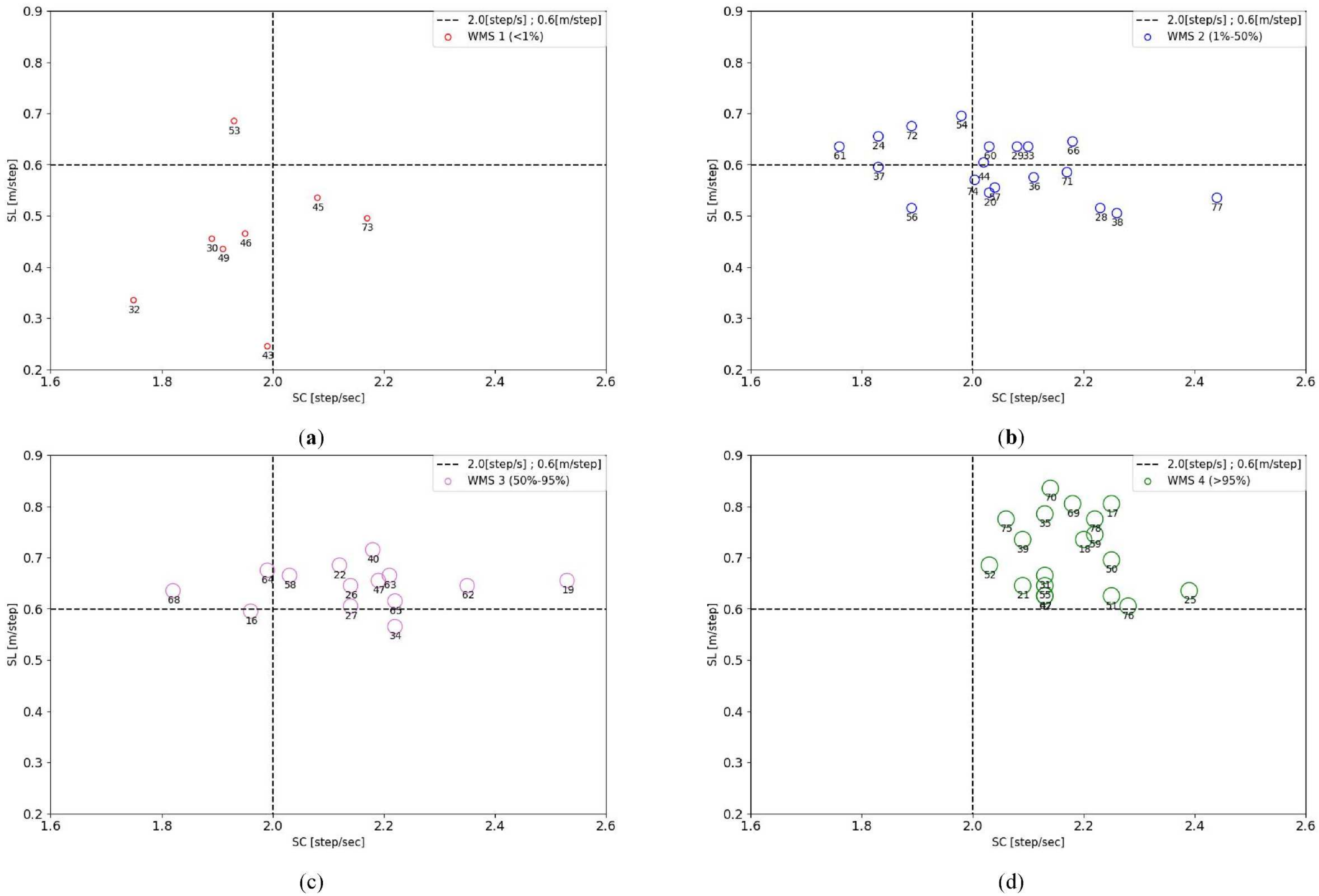


Figure 4.7 SC and SL distribution map: (a) shows the WMS1; (b) shows the WMS2; (c) shows the WMS3; and (d) shows the WMS4.

Figure 4.8 shows the percentage distribution of the four WMS scores in the four gait performance ranges. WMS1 individuals are located in 62.5% in Range III, while 12.5% are in Range II and 25.0% in Range IV. All WMS4 cases are in Range I. In addition, 71.4% of WMS3 and 26.3% of WMS2 individuals are also located in Range I, indicating that although their gait performance appears normal, their muscle strength is relatively low.

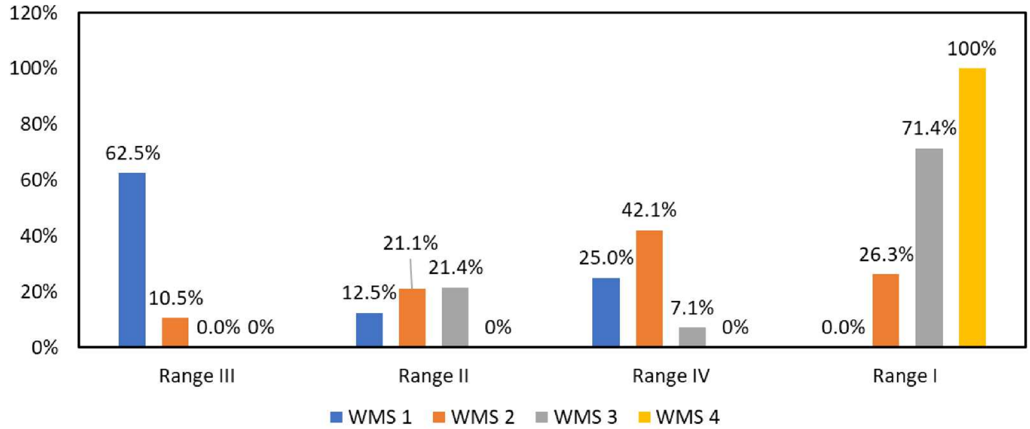


Figure 4.8 Percentages of the four WMS scores in these four ranges.

Figure 4.9 shows the distribution of 6MWD among the four WMS scores, with almost all of the 6MWD of individuals in WMS4 above 400m, and all below 300m in WMS1.

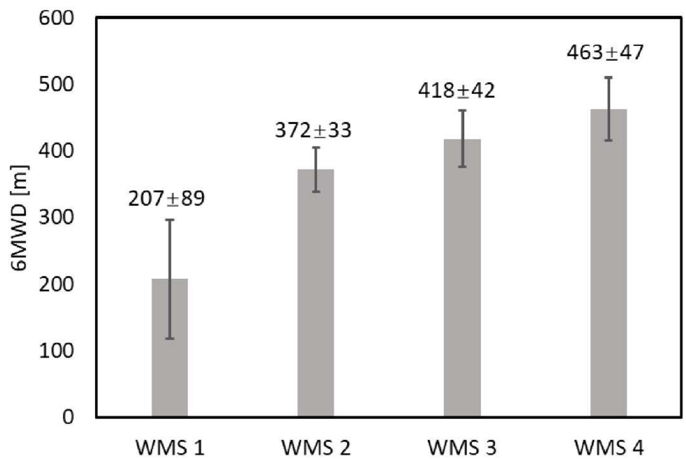


Figure 4.9 Distribution of 6MWD in four WMS scores.

4.3.5 WMS score with gait distribution map and frailty

Figure 4.10 replots Figure 3.5 (Chapter 3) using WMS scores. The size of each marker represents the four levels of muscle strength, while the patients judged by the J-CHS criteria are described in different colors: frail in red, pre-frail in blue, and non-frail in green. Most WMS4 individuals are located in Range I, mainly consisting of non-frail participants and some pre-frail individuals. Most WMS1 individuals are located in Range III, where the majority are frail, with a few pre-frail cases.

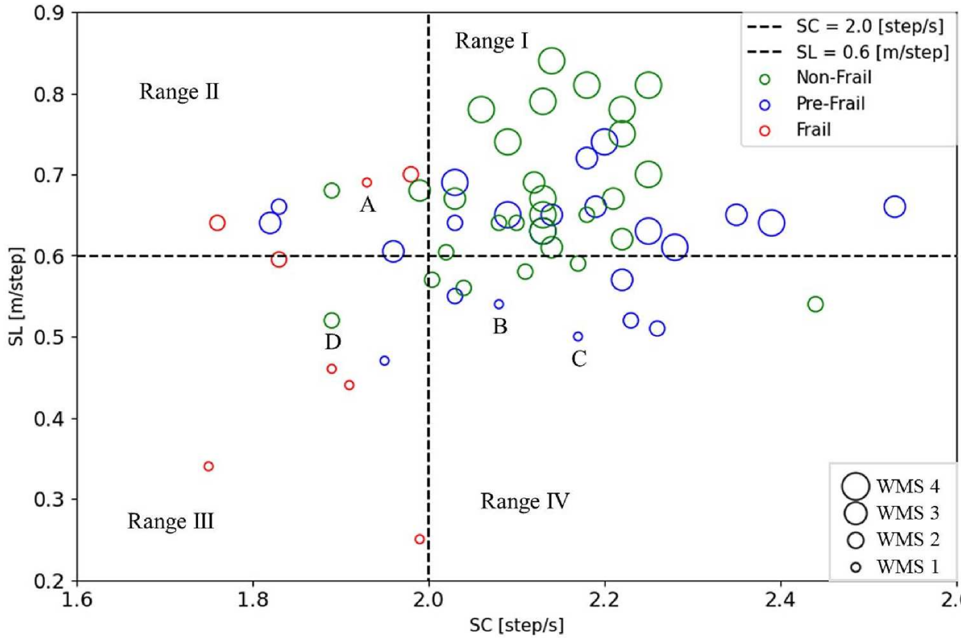


Figure 4.10 Replot of Figure 3.5 (Chapter3) using the WMS scale. Marker size denotes muscle strength levels, and color indicates frailty by the J-CHS assessment (red as frail cases, blue as pre-frail cases, and green as non-frail cases).

Figure 4.11 shows the percentage of each J-CHS assessment result within the four WMS score categories. 62.5% of frail individuals were classified as WMS1, and the remaining 37.5% were in WMS2. For pre-frail and non-frail individuals, their percentages increased gradually from lower to higher WMS levels, according to our defined WMS scores. 41.4% of non-frail individuals and 30.4% of pre-frail individuals were concentrated in WMS4.

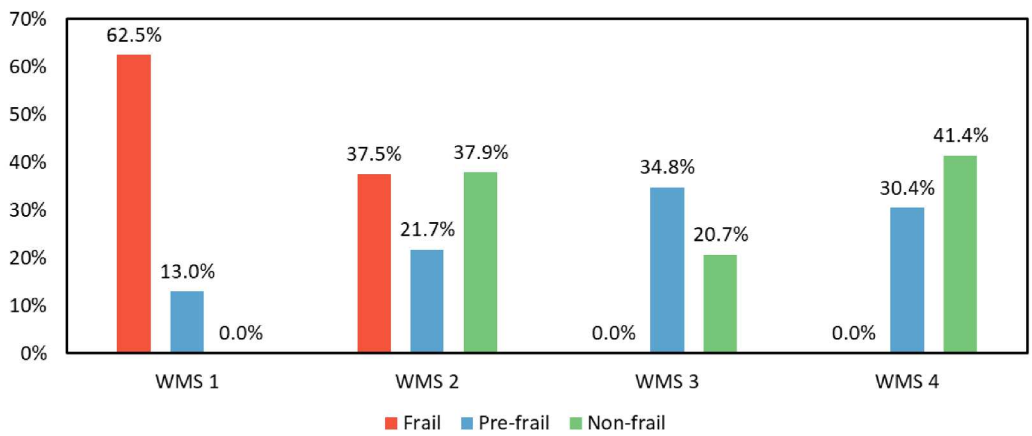


Figure 4.11 Percentages of the J-CHS assessment results in each of the four WMS scores.

4.4 Discussion

This chapter proposes a novel method to quantify lower limb muscle weakness in old people by combining the gait parameters of SC, SL, and 6MWEE in 6MWT. A new index called the WMS score has been developed to comprehensively evaluate lower limb muscle capacity. This method allows for a more accurate analysis of muscle condition and strength differences reflected by walking performance, providing reliable information for the early detection of sarcopenia and frailty, as well as the assessment of intervention and rehabilitation effectiveness.

This study involved 60 older adults as participants and classified their sarcopenia status based on the AWGS criteria. Among them, 10 individuals were identified as having sarcopenia. Table 4.1 shows that the 6MWT gait parameters in the sarcopenia group were all lower than those in the non-sarcopenia group, with significant differences, demonstrating that gait parameters are effective indicators of muscle function and play an important role in assessing muscle strength. Table 4.2 shows that among the 10 sarcopenia cases, most were categorized as frail, with a few classified as pre-frail. This further supports the viewpoint presented in Chapter 3, which suggests that frailty is often a direct reflection of muscle weakness. Based on the evaluation of frailty and sarcopenia according to the AWGS and J-CHS criteria, we found that SC, which is associated with reduced fatigue, SL, which correlates with longer walking distances, and 6MWEE, which reflects muscle work efficiency, are all effective indicators for assessing exercise endurance.

We constructed the WMS index using SL, SC, and 6MWEE to develop a quantitative measure that comprehensively reflects muscle strength during walking. The WMS index was obtained through multiple regression analysis and showed a high degree of correlation in the 3D scatter plot ($r = 0.853$). We then examined the relationship between WMS and clinical physical indicators. Among them, 6MWD ($r = 0.914$) and GV ($r = 0.858$) showed very strong correlations, while HS ($r = 0.574$) showed only a moderate correlation. This is because our focus is on evaluating lower limb muscle function through 6MWT, which is not directly related to the upper limbs, although stronger lower limb function often corresponds to greater HS.

We proposed the concept of scoring the WMS for the quantification of walking muscle strength. Four scales were defined from Equation (4.5) as WMS1 (<0.01), WMS2 (0.01~0.50), WMS3 (0.50~0.95), and WMS4 (>0.95), which were visualised by gait distribution map displaying the lower limb muscle capacity. WMS1 scores were mostly concentrated in Range III (SC < 2.0 [step/s], SL < 0.6 [m/step]), while WMS4 scores were mainly located in Range I, showing a combination of high SC and high SL, which suggests that the gait distribution map aligns well with muscle function grading. Compared to the J-CHS results, the WMS scores showed that 62.5% of frail and 13.0% of pre-frail patients scored WMS1, while 41.4% of non-frail and 30.4% of pre-frail patients scored WMS4. Furthermore, the average 6MWD values corresponding to WMS1~4 were 207 m, 372 m, 418 m, and 463 m, respectively. The 6MWD of all patients scored as WMS1 was lower than 300 m (or 330 meters by another threshold), which was the cutoff value for the survival rate [27] and high fall risk [28]. The 6MWD of all patients with a WMS4 score was higher than 400 m, which was the cutoff value to have a low risk of cardiovascular disease [26].

Looking at individual examples in Figure 4.10, patients A and B were both scored as WMS1 but belonged to different ranges: Range II and Range IV, respectively. They were terminated from the experiment due to increased heart rate and shortness of breath during the 6MWT. Patient C's score was WMS1, and they were diagnosed with sarcopenia (HS = 25.85 [kg], GV = 0.92 [m/s], and SMI = 5.5 [kg/m2]) based on the AWGS criteria. Interestingly, patient D's score as WMS2 was in Range III and was judged as non-frail by the J-CHS. This patient's five-meter walking speed was 1.29 [m/s], which was higher than the J-CHS speed criteria. However, this patient's walking speed of each 20m in 6MWT varied greatly, and its average speed was 0.98 ± 0.19 [m/s] lower than the J-CHS standard. Additionally, patient D's 6MWD was 306 m.

The WMS scoring system introduced in this chapter, together with the SC-SL gait distribution map described in Chapter 3, provides a new and practical method for evaluating lower limb muscle condition and quantifying muscle strength in older adults. Most individuals located in Range III of the distribution map and scored as WMS1 met the diagnostic criteria for sarcopenia and frailty, confirming the clinical applicability and discriminative power of this method. Therefore, both the WMS score and the SC-SL gait map show strong potential for early identification of sarcopenia and physical frailty. Moreover, different patients diagnosed with sarcopenia and frailty exhibit varying WMS index, providing a quantifiable basis for designing personalised intervention programs for elderly individuals. Further validation suggests that this approach may serve as an effective tool for guiding elderly rehabilitation.

4.5 Conclusion

This chapter proposed a novel WMS scoring method for quantitatively evaluating lower limb muscle weakness, combining SC, SL, and 6MWEE in the 6MWT. The results showed that gait parameters in individuals with sarcopenia were significantly lower than those without the condition. The WMS score showed correlation with traditional indicators such as 6MWD, GV, and HS, confirming its good discriminative ability, and Four-level WMS scores clearly reflected differences in muscle capacity. In particular, the close overlap between WMS1 and Range III in the SC-SL distribution map suggests that individuals with poor gait performance often exhibit signs of sarcopenia and frailty, highlighting its clinical application value. This method provides a new objective quantitative tool for early detection, intervention application, and improvement effects of frailty and sarcopenia in older adults, and offers a theoretical foundation and practical direction for future rehabilitation and health management strategies.

References

[1] Manrique-Espinoza B, Salinas-Rodríguez A, Rosas-Carrasco O, et al. Sarcopenia is associated with physical and mental components of health-related quality of life in older adults[J]. Journal of the American medical directors association, 2017, 18(7): 636. e1-636. e5.

[2] Rizzoli R, Reginster J Y, Arnal J F, et al. Quality of life in sarcopenia and frailty[J]. Calcified tissue international, 2013, 93: 101-120.

[3] Chen L K, Woo J, Assantachai P, et al. Asian Working Group for Sarcopenia: 2019 consensus update on sarcopenia diagnosis and treatment[J]. Journal of the American Medical Directors Association, 2020, 21(3): 300-307. e2.

[4] Studenski S, Perera S, Wallace D, et al. Physical performance measures in the clinical setting[J]. Journal of the American Geriatrics Society, 2003, 51(3): 314-322.

[5] Mong Y, Teo T W, Ng S S. 5-repetition sit-to-stand test in subjects with chronic stroke: reliability and validity[J]. Archives of physical medicine and rehabilitation, 2010, 91(3): 407-413.

[6] Lauretani F, Ticinesi A, Gionti L, et al. Short-Physical Performance Battery (SPPB) score is associated with falls in older outpatients[J]. Aging clinical and experimental research, 2019, 31: 1435-1442.

[7] Rodrigues F, Domingos C, Monteiro D, et al. A review on aging, sarcopenia, falls, and resistance training in community-dwelling older adults[J]. International journal of environmental research and public health, 2022, 19(2): 874.

[8] Trierweiler H, Kisielewicz G, Hoffmann Jonasson T, et al. Sarcopenia: a chronic complication of type 2 diabetes mellitus[J]. Diabetology & metabolic syndrome, 2018, 10: 1-9.

[9] Bone A E, Hepgul N, Kon S, et al. Sarcopenia and frailty in chronic respiratory disease: Lessons from gerontology[J]. Chronic respiratory disease, 2017, 14(1): 85-99.

[10] Goates S, Du K, Arensberg M B, et al. Economic impact of hospitalizations in US adults with sarcopenia[J]. The Journal of frailty & aging, 2019, 8(2): 93-99.

[11] Rizzoli R, Reginster J Y, Arnal J F, et al. Quality of life in sarcopenia and frailty[J]. Calcified tissue international, 2013, 93: 101-120.

[12] Offord N J, Clegg A, Turner G, et al. Current practice in the diagnosis and management of sarcopenia and frailty–results from a UK-wide survey[J]. Journal of frailty, sarcopenia and falls, 2019, 4(3): 71.

[13] Greco E A, Pietschmann P, Migliaccio S. Osteoporosis and sarcopenia increase frailty syndrome in the elderly[J]. Frontiers in endocrinology, 2019, 10: 255.

[14] Dolinsky V W, Jones K E, Sidhu R S, et al. Improvements in skeletal muscle strength and cardiac function induced by resveratrol during exercise training contribute to enhanced exercise performance in rats[J]. The Journal of physiology, 2012, 590(11): 2783-2799.

[15] Marzetti E, Calvani R, Tosato M, et al. Physical activity and exercise as countermeasures to physical frailty and sarcopenia[J]. Aging clinical and experimental research, 2017, 29: 35-42.

[16] Joppa P, Tkacova R, Franssen F M E, et al. Sarcopenic obesity, functional outcomes, and systemic inflammation in patients with chronic obstructive pulmonary disease[J]. Journal of the American medical directors association, 2016, 17(8): 712-718.

[17] Westerterp K R. Physical activity and physical activity induced energy expenditure in humans: measurement, determinants, and effects[J]. Frontiers in physiology, 2013, 4: 90.

[18] Umberger B R, Gerritsen K G M, Martin P E. A model of human muscle energy expenditure[J]. Computer methods in biomechanics and biomedical engineering, 2003, 6(2): 99-111.

[19] 体成分分析装置：https://www.medister.info/body_composition_analyzer/5918/, (accessed on 8 June 2025).

[20] Hargreaves M, Spriet L L. Skeletal muscle energy metabolism during exercise[J]. Nature metabolism, 2020, 2(9): 817-828.

[21] Hills A P, Mokhtar N, Byrne N M. Assessment of physical activity and energy expenditure: an overview of objective measures[J]. Frontiers in nutrition, 2014, 1: 5.

[22] Yamamura C, Tanaka S, Futami J, et al. Activity diary method for predicting energy expenditure as evaluated by a whole-body indirect human calorimeter[J]. Journal of nutritional science and vitaminology, 2003, 49(4): 262-269.

[23] Harris J A, Benedict F G. A biometric study of human basal metabolism[J]. Proceedings of the National Academy of Sciences, 1918, 4(12): 370-373.

[24] Brooks A G, Gunn S M, Withers R T, et al. Predicting walking METs and energy expenditure from speed or accelerometry[J]. Medicine and Science in Sports and Exercise, 2005, 37(7): 1216-1223.

[25] Jetté M, Sidney K, Blümchen G. Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity[J]. Clinical cardiology, 1990, 13(8): 555-565.

[26] Newman A B, Simonsick E M, Naydeck B L, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability[J]. Jama, 2006, 295(17): 2018-2026.

[27] Demir R, Küçükoğlu M S. Six-minute walk test in pulmonary arterial hypertension[J]. Anatolian journal of cardiology, 2015, 15(3): 249.

[28] Six-Minute Walking Distance Predicts Fall Risk in Elderly Patients Hospitalized for Heart Failure. Available online: https://www.jstage.jst.go.jp/article/jalliedhealthsci/8/2/8_110/_pdf/-char/ja (accessed on 20 April 2025).

Chapter 5 Gait pattern distribution and walking suggestions

5.1 Overview

Although the decline in muscle function with age has been widely recognized, its impact is often not limited to the muscles alone. This process is usually accompanied by a series of negative health outcomes, such as frailty, sarcopenia, falls, and fractures, which can significantly affect the quality of life and independence of older people. Studies have shown that physical activity plays a crucial role in healthy aging, and maintaining adequate activity levels becomes especially important as these conditions develop [1, 2, 3]. While physical activity may have only indirect effects on some aspects of health, its impact on improving muscle mass and strength is both direct and significant. Previous research has confirmed that a lack of physical activity is a major risk factor for sarcopenia, while moderate activity, especially exercise that includes strength training, can effectively improve muscle mass and strength [4, 5]. Therefore, staying physically active is closely linked to reducing the risk of sarcopenia, and resistance training, in particular, is widely considered one of the most effective strategies for preventing and slowing down the decline in muscle capacity.

Walking is considered one of the simplest and most accessible forms of physical activity, especially for older adults. As a low-intensity, aerobic exercise, walking is easy to perform daily and is hardly limited by time, location, or financial conditions. Therefore, it has wide practical value in promoting health among the elderly. Many studies have confirmed that walking plays a positive role in maintaining and improving lower limb muscle strength [6, 7, 8].

The 6-minute walk test (6MWT) is a standard clinical assessment widely used to evaluate an individual's cardiopulmonary endurance and functional status, with significant application value among elderly adults, patients with chronic diseases, and those undergoing rehabilitation [9, 10]. In clinical rehabilitation, the test primarily focuses on the total distance walked within six minutes (6MWD) as the key indicator for assessing physical fitness or functional recovery [11, 12]. For elderly individuals with relatively healthy muscle function, this mean-based distance measurement is feasible and informative. However, for those with weaker muscle function, their gait performance often falls below the commonly used cut-off values of 400 m or even 300 m [13, 14], making it difficult to provide suitable guidance for individuals with different walking capacities. Therefore, while the 6MWT is an effective tool in clinical practice, its application remains limited, particularly in guiding walking or rehabilitation training based on the test results. Doctors' walking advice is often vague and lacks improvement programmes based on objective, quantifiable data.

In recent years, some researchers have come to realize that simply aiming to increase walking distance may not be the most clinically meaningful goal in walking assessments and training. Compared to "walking farther," "walking properly" may better reflect an individual's actual functional status and rehabilitation potential [15]. Specifically, gait quality during walking, such as stride length control, stride cadence rhythm, and lower limb flexion angles, can be more sensitive indicators for evaluating lower limb muscle capacity and predicting health risks [16]. For example, even if a person walks at a slower speed, maintaining a relatively large distance or consistent leg flexion with each stride may be more effective for improving muscle strength than walking fast with poor quality. This perspective is especially important for older adults, as those with already weak muscles or movement difficulties may experience greater fatigue or face a higher risk of falling if they push themselves to walk longer distances without proper form.

Currently, using devices such as cameras to identify gait characteristics is a common approach [17]. However, this is usually limited to analysing short distances or only a few gait cycles, which may not reflect most gait states in daily life. Additionally, gait analysis methods based on multiple sensors are often confined to laboratory settings [18] and may pose an inconvenience for elderly individuals in their daily walking activities. Another issue is that the 6MWT must be conducted in a designated space, as observers calculate the 6MWD using fixed walking tracks and ground markers [19]. This presents a challenge for healthcare institutions with limited space. Furthermore, current methods for measuring stride length are usually restricted to calculating the average over a fixed distance, which makes it difficult to capture individual gait variations when the distance is unknown.

In the previous chapters, we discussed how gait patterns obtained from the 6MWT can be used to evaluate walking-related muscle status and quantify lower limb muscle weakness. To further support older adults in achieving the goal of "walking properly," and address the above issues, this chapter presents a new algorithm that utilizes the 6MWT acceleration data to calculate the leg swing angle and stride distance, and introduce a novel evaluation method for visualizing gait performance. Different from traditional methods that focus on average indicators, this approach emphasizes the dynamic changes and distribution characteristics of gait parameters during the 6MWT, providing more detailed gait analysis data, helping physicians make more accurate suggestions based on objective data, and promoting safe and efficient walking performance in the elderly. This approach not only helps maintain and improve lower limb muscle function but also provides an important basis for developing high-quality, personalized walking training plans in rehabilitation and health management.

5.2 Gait parameters

5.2.1 Extraction of gait parameters

In Chapter 2, we introduced four parameters related to the 6MWT: step length (SL), step cadence (SC), gait velocity (GV), and walking distance (6MWD). These parameters were calculated based on the average values during the 20-meter straight walking part, as shown in the 6MWT guideline in Figure 2.5 [19]. In this Chapter, to better analyse the gait performance of old people, we instead turn our focus to a detailed analysis of each stride, extracting the gait parameters for each stride. Figure 5.1 presents a complete schematic of walking kinematics, illustrating the movement of one lower limb starting from a vertical position, going through the swing, and finally returning to the vertical position. Among these, the push-off phase and the forward swing phase are the most critical, as they involve the control of the posture angles of the lower leg and thigh, and are closely related to the distance and time required to complete each stride.

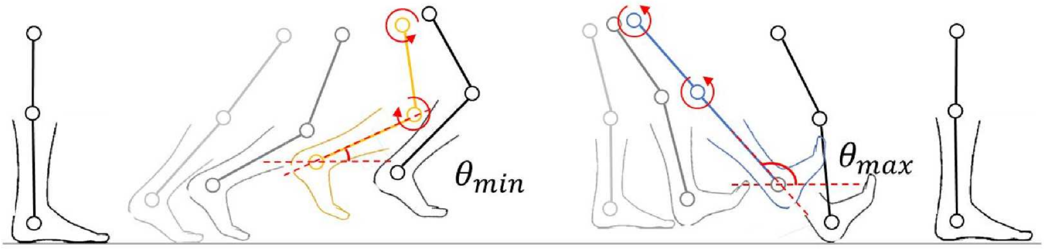


Figure 5.1 Schematic of kinematic analysis of a walking cycle

Since the sensor in this study was placed only on the ankle, it was not possible to directly obtain the thigh posture angle. Therefore, we used a characteristic of the walking process where the thigh and lower leg are nearly aligned in a straight line when the lower leg reaches its maximum forward position (Figure 5.1), and used the maximum forward angle of the lower leg as a substitute indicator for the thigh posture angle.

In this chapter, we mainly extracted the following parameters for each stride: maximum posterior shank angle (PSA), maximum anterior shank angle (ASA), distance, and time. Then, gait velocity (distance/time) and the angle range (maximum ASA - maximum PSA) were used to reflect dynamic changes during walking.

5.2.2 Problem

As everyone knows, angle can be calculated using trigonometric relationships of acceleration, and distance can be obtained through double integration. However, since this study used a three-axis inertial acceleration sensor, the measured data included both the acceleration due to walking and gravitational acceleration, so it is difficult to accurately reproducible the required angles and distances directly using the above method.

The first problem we want to solve is to estimate the attitude angle of the sensor during walking. Among existing technical approaches, the acceleration-based filtering angle algorithm (AFA) and the multi-sensor fusion angle algorithm (MSA) are two widely used solutions [20, 21]. AFA has the advantage of being simple to implement. It estimates angles by taking advantage of the fact that gravitational acceleration changes slowly and has low frequency, filtering out high-frequency components. However, its accuracy can be easily affected by rapid movement and noise during dynamic walking, leading to larger errors. On the other hand, MSA combines data from an accelerometer, gyroscope, and magnetometer, and uses mathematical models to update the posture estimation dynamically, resulting in more accurate angle measurements. This method is widely used in posture control. However, it is not suitable for this study, as we only collected walking acceleration data from older adults.

The second problem we have to address is to calculate the walking distance for each stride. Trentzsch and colleagues proposed a method called the synthesized acceleration algorithm (SAA) to estimate walking distance, and confirmed that its results correlate with GPS measurements [22]. The SAA method combines acceleration signals collected from the three axes of the sensor, subtracts the effect of 1g gravitational acceleration, and uses the principle of zero-velocity update during each step to estimate stride length. Although this method shows a certain level of accuracy in distance estimation, its limitation is that it cannot provide information about gait angles.

In this chapter, we propose a new method of the coordinate transformation angle algorithm (CTAA), which estimates both angle and distance during walking. To verify the effectiveness of CTAA, we compare its angle estimation results with those from the traditional AFA and MSA methods. At the same time, we compare its distance estimation results with those from the SAA method. These comparisons aim to validate the accuracy and practical value of the CTAA method for angle and distance estimation.

5.3 Methodology

5.3.1 Experimental design

We wore the wearable acceleration sensor developed in this study and a WIT 9-axis inertial sensor (WIT Intelligent Technology Ltd, China) on the ankles of three students. Data were collected under three self-selected walking speeds: fast, normal, and slow. Then, the collected data were processed using the AFA and MSA methods to calculate and verify the posture angles, to evaluate the accuracy and feasibility of the CTAA method proposed in this study.

5.3.2 Introduction to AFA, MSA, and SAA methods

(1) The AFA method applies low-pass filtering to the acceleration signal to remove high-frequency noise and extract the main low-frequency component caused by gravity. Based on this component, the sensor's pitch angle can be estimated using Equation (5.1). In the calculation, the acceleration values in the y-axis and z-axis directions of the sensor are typically used, and the angle is obtained through the arctangent function.

$$\theta = arctan\,(\frac{az}{ay}) \tag{5.1}$$

(2) The MSA method mainly fuses data from three types of sensors, accelerometer, gyroscope, and magnetometer, to continuously estimate the sensor's orientation, including pitch, roll, and yaw angles. In this study, we focus only on explaining the pitch angle, which is described in three steps. First, when the sensor is at rest, the three-axis acceleration values are obtained from the raw data to perform a static estimation, as shown in Equation (5.2).

$$\theta_{acc} = arctan\,(\frac{-az}{\sqrt{ax^2 + ay^2}}) \tag{5.2}$$

Then, the pitch angle (rotation around the x-axis) is obtained by integrating the angular velocity signal from the gyroscope during walking, as shown in Equation (5.3).

$$\theta_{gyro}(t) = \theta(t-1) + \omega_x(t) \cdot dt \tag{5.3}$$

Finally, to reduce the effects of acceleration noise and gyroscope drift, the two estimation results are combined using a complementary filter, as shown in Equation (5.4), to obtain the final pitch angle estimate. In this equation, α is a weighting factor, usually set between 0.90 and 0.98.

$$\theta_{fused}(t) = \alpha \cdot \theta_{gyro}(t) + (1-\alpha) \cdot \theta_{acc}(t) \tag{5.4}$$

(3) The SAA method first applies appropriate filtering to the three components of acceleration to remove noise, and then calculates the total acceleration using Equation (5.5).

$$a(t) = \sqrt{ax(t)^2 + ay(t)^2 + az(t)^2} \tag{5.5}$$

Then, based on the zero-velocity update principle for each step, 1g of gravitational acceleration is subtracted from the combined acceleration in each cycle, and the distance is calculated through double integration as in Equation (5.6).

$$s(t) = \iint (a(t) - 1) d^2 t \tag{5.6}$$

5.3.3 Principles of the CTAA method

5.3.3.1 Mathematical modelling of angle

The angle between the lower leg and the ground during walking changes in a periodic pattern. As shown in Figure 5.2, the angle change can be divided into three stages:

Stage 1: This stage begins when the lower leg is perpendicular to the ground, with an angle of about 90°. Then, as the body's center of mass moves forward, the lower leg swings backward, gradually reaching the maximum PSA.

Stage 2: After reaching the maximum PSA position, the lower leg starts to swing forward, accelerating past the vertical position until it reaches the maximum ASA.

Stage 3: After the lower leg reaches its maximum ASA, it begins to decelerate and swing back, eventually returning to the vertical position in preparation for the next stride.

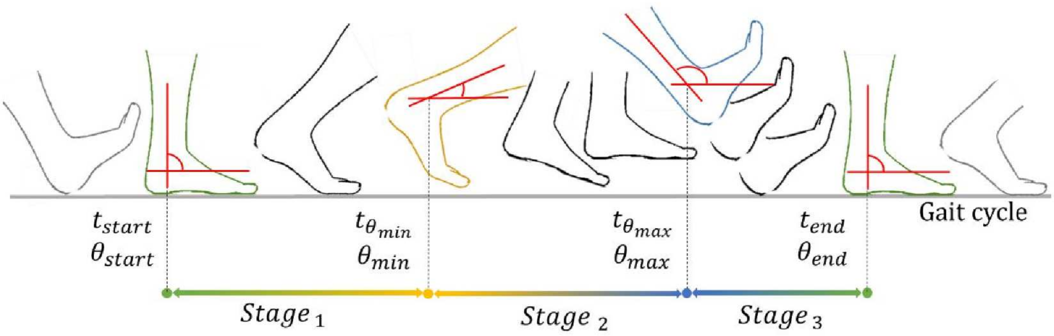


Figure 5.2 Schematic of the change in the angle of the lower leg to the ground

Although the exact timing and magnitude of the maximum PSA and ASA during walking are unknown, they can still be described using a mathematical model, as shown in Equation (5.7).

$$\theta(t) = \begin{cases} S_1(t), & t \in [t_{start}, t_{\theta_{min}}] \\ S_2(t), & t \in [t_{\theta_{min}}, t_{\theta_{max}}] \\ S_3(t), & t \in [t_{\theta_{max}}, t_{end}] \end{cases} \tag{5.7}$$

where $S_1(t)$, $S_2(t)$, and $S_3(t)$ represent the 3 stages depicted in Figure 5.2, respectively. t_{start} and t_{end} are the times of the start and the end of each walk cycle. $t_{\theta_{min}}$ and $t_{\theta_{max}}$ are the times of the maximal PSA and ASA state.

After reviewing related studies, we found that the shank inclination angle shows an approximately linear trend during the three phases of the walking cycle. Specifically, starting from the vertical position relative to the ground, the angle gradually decreases to reach the maximum PSA in stage 1; then, in stage 2, the angle linearly increases from the maximum PSA to the maximum ASA; finally, in stage 3, the angle linearly returns to the initial vertical position. We used a third-order polynomial to fit this trend, as shown in Equation (5.8), to reproduce the variation of the shank-ground angle during the walking cycle.

$$\theta(t) = a_i + b_i \cdot (t - t_i) + c_i \cdot (t - t_i)^2 + d_i \cdot (t - t_i)^3 \tag{5.8}$$

Next, boundary conditions are imposed on the model as in Equation (5.9).

$$\begin{cases} \theta_{start} = \theta_{end} = 90° \\ \theta_{min} < 90°, \theta_{max} > 90° \\ t_{\theta_{min}} < t_{\theta_{max}} \end{cases} \tag{5.9}$$

Finally, the times of maximum PSA and maximum ASA states of the model are smoothed as in Equation (5.10).

$$\begin{cases} S_1'(t_{\theta_{min}}) = S_2'(t_{\theta_{min}}) \\ S_2'(t_{\theta_{max}}) = S_3'(t_{\theta_{max}}) \end{cases}, \begin{cases} S_1''(t_{\theta_{min}}) = S_2''(t_{\theta_{min}}) \\ S_2''(t_{\theta_{max}}) = S_3''(t_{\theta_{max}}) \end{cases} \tag{5.10}$$

5.3.3.2 Prediction of the timing of maximum PSA and ASA

The first problem we address is predicting the timing of the maximum PSA and ASA. Figure 5.3 shows the relationship between acceleration data and gait kinematic analysis. In this figure, we redefined the walking cycle by marking the beginning and end of a step when the shank is vertical at 90°, instead of using the moment the foot contacts the ground as described in Chapter 2.

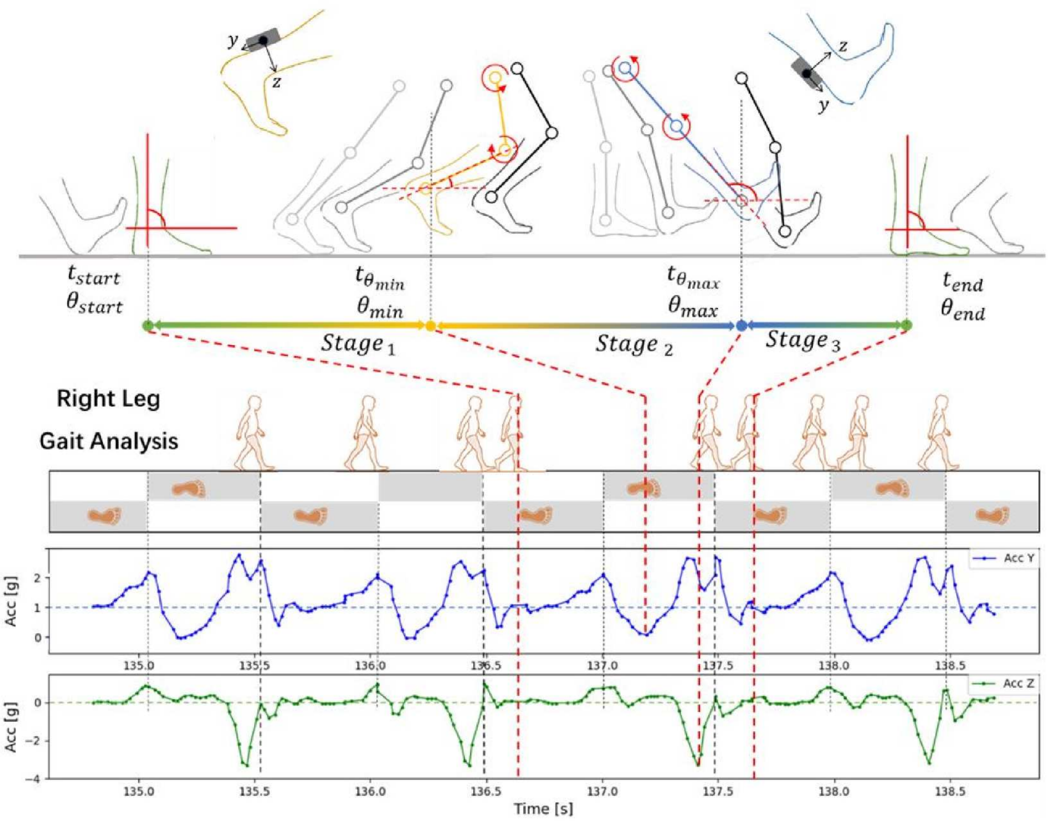


Figure 5.3 Acceleration changes and walking kinematics analysis.

When the shank swings to reach the maximum PSA, the y-axis direction of the sensor worn on the ankle gradually shifts from its original vertical downward position toward the opposite direction of walking. Since gravity is always present and directed downward, this change in sensor orientation causes the gravitational component sensed along the y-axis to decrease gradually and approach zero. As shown in the trend of y-axis acceleration in Figure 5.3, the moment when the y-axis acceleration reaches its minimum value corresponds to the occurrence of the maximum PSA.

On the other hand, during the transition from stage 2 to stage 3 of the gait cycle, the leg experiences a shift from forward acceleration to backward deceleration. Since the inertial sensor has a reactive force response to changes in acceleration, the acceleration value in the z-axis direction will then first peak in the negative direction and then fall back. Therefore, as shown in the waveform of the z-axis acceleration in Figure 5.3, the moment when the z-axis acceleration reaches its minimum value corresponds to the time when the shank reaches the maximum ASA.

The analysis of Figure 5.3 shows that by observing the local minimum points of the y-axis and z-axis in the acceleration data, it is possible to predict the timing of the maximum PSA and ASA. This provides a foundation for estimating the angles.

5.3.3.3 Principles of estimation of maximum PSA and ASA

One problem we still have unresolved is that the size of the maximum PSA and ASA is unknown.

In gait analysis, a walking cycle is typically divided into two main phases: the swing phase and the stance phase. The stance phase refers to the period when the foot is in contact with the ground and bearing weight. As shown in Figure 5.3, at the end of each walking cycle, during the stance phase, the acceleration data from the sensor fluctuates around zero. This indicates that the sensor is in a relatively stationary state and the foot is not moving. Since acceleration represents the rate of change in velocity, when acceleration approaches zero, it suggests that the instantaneous velocity of the foot is also close to or equal to zero. This is the principle of zero velocity updating commonly used in gait analysis.

Based on these observations, we can predefine a range for the maximum PSA and ASA values. Then, by converting the sensor's coordinate system to a global coordinate system, subtracting 1g of gravitational acceleration from the vertical direction, and integrating the vertical and forward-direction acceleration, we can estimate the speed. When both components of velocity approach zero, the predefined values can be considered as the correct maximum PSA or ASA. At this point, by further integrating the forward-direction acceleration, we can calculate the walking distance for each step.

5.3.4 Technology roadmap of the CTAA method

Figure 5.4 shows the technology roadmap for extracting gait parameters, which is divided into seven steps.

(1) Walking data of older adults is collected using an inertial acceleration sensor. A simple preprocessing is applied using a 5-point moving average method to reduce noise.

(2) The preprocessed data is then segmented into gait cycles. Figure 5.4 shows the y-axis and z-axis accelerations during a gait cycle. The key time points are marked with asterisks including the start and end of the cycle and the time of maximum PSA and ASA.

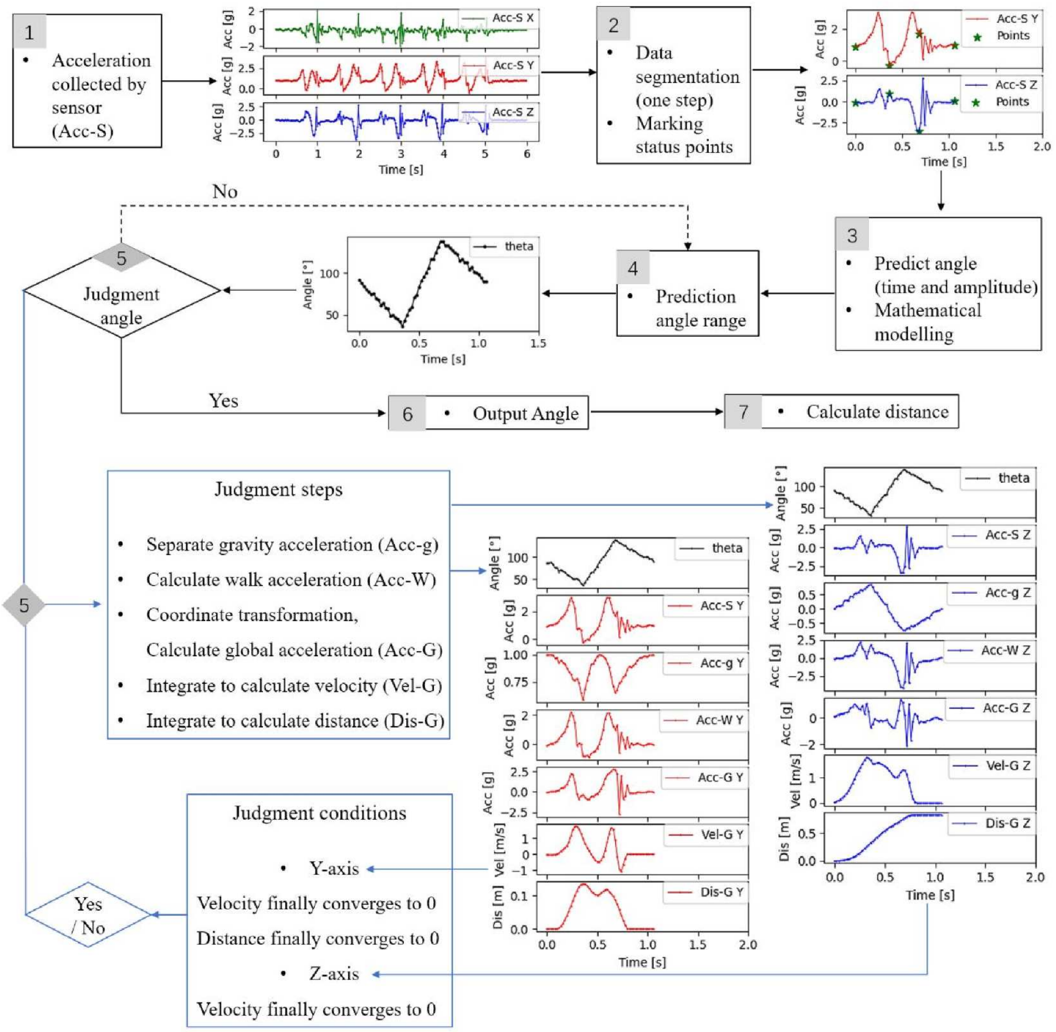


Figure 5.4 Technology roadmap for extracting gait parameters, which is divided into seven steps. Step 5 gives a detailed description and shows the data in the Y and Z directions when the angle prediction is successful. From top to bottom, they are: angle; acceleration data after preprocessing; component of gravitational acceleration in the sensor coordinate system (obtained by the trigonometric relation between gravitational acceleration and angle); true walking acceleration (acceleration data after preprocessing - component of gravitational acceleration in the sensor coordinate system); walking acceleration in the global coordinate system; velocity in the global coordinate system; and distance in the global coordinate system.

(3) For $t_{start}, t_{end}, \theta_{start} = 90°, \theta_{end} = 90°, t_{\theta_{min}} = t_{AccY_{min}}, t_{\theta_{max}} = t_{AccZ_{min}}$, which are obtained from step (2), substitute them into mathematical model shown in Equation (5.7).

(4) The angle values of the maximum PSA and ASA are preset, the range of values are used as $\theta_{min} \in (10°\sim89°)$; $\theta_{max} \in (91°\sim160°)$, respectively, and a matrix is built as in Equation (5.11).

$$(\theta_{min}, \theta_{max})_{i\times j} = \begin{pmatrix} (10°, 91°) & (10°, 92°) & \cdots & (10°, 160°) \\ (11°, 91°) & (11°, 92°) & \cdots & (11°, 160°) \\ \vdots & \vdots & \ddots & \vdots \\ (89°, 91°) & (89°, 92°) & \cdots & (89°, 160°) \end{pmatrix} \tag{5.11}$$

where $(\theta_{min}, \theta_{max})$ are the angles between the lower leg and the ground at maximum PSA and maximum ASA.

(5) During walking, the zero velocity update principle is used to predict the angle. First, as shown in Figure 5.5, the sensor coordinate system is transformed into the global coordinate system. This process is divided into two parts based on whether $\theta \leq \frac{\pi}{2}$ and $\theta > \frac{\pi}{2}$, as described in Equation (5.12).

$$\begin{aligned} \theta \leq \frac{\pi}{2}, \quad & \begin{cases} a_Z^{global} = a_z^{sensor} \cdot cos(\alpha) - a_y^{sensor} \cdot sin(\alpha) \\ a_Y^{global} = a_z^{sensor} \cdot sin(\alpha) + a_y^{sensor} \cdot cos(\alpha) - G \end{cases} \\ \theta > \frac{\pi}{2}, \quad & \begin{cases} a_Z^{global} = a_z^{sensor} \cdot cos(\beta) + a_y^{sensor} \cdot sin(\beta) \\ a_Y^{global} = -a_z^{sensor} \cdot sin(\beta) + a_y^{sensor} \cdot cos(\beta) - G \end{cases} \end{aligned} \tag{5.12}$$

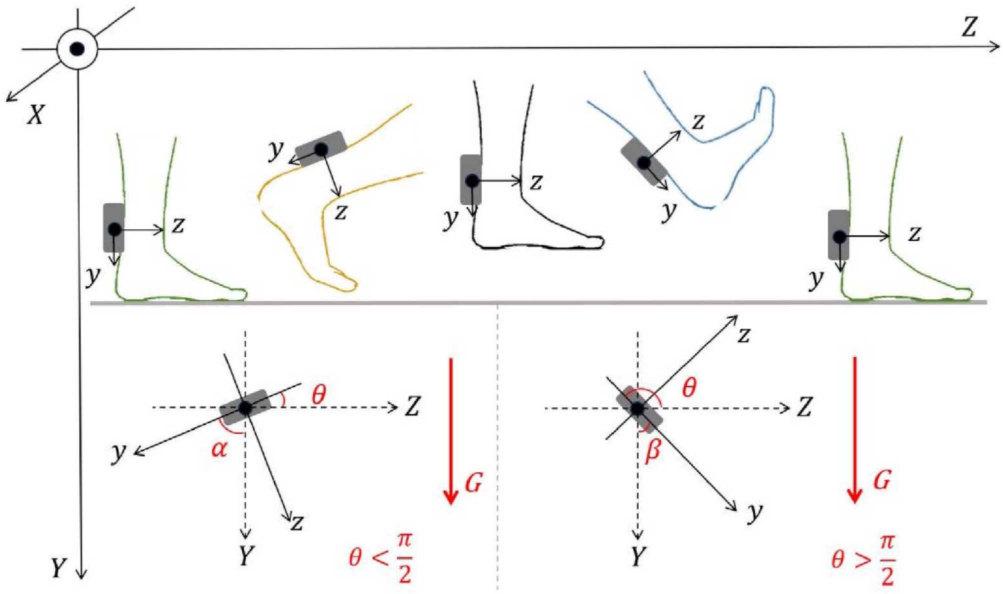


Figure 5.5 Schematic diagram of sensor coordinate system conversion to global coordinate system.

According to the global coordinate system shown in Figure 5.5, the acceleration of Equation (5.12) is used to calculate the velocity in the Y and Z directions as shown in Equation (5.13).

$$\begin{aligned} v_Y^{global}(end) &= \int_{t_{start}}^{t_{end}} a_Y^{global} \cdot dt \\ v_Z^{global}(end) &= \int_{t_{start}}^{t_{end}} a_Z^{global} \cdot dt \end{aligned} \tag{5.13}$$

Substitute the preset value of $(\theta_{min}, \theta_{max})|_{i=i_0,j=j_0}$ in step (4) into the model, and when the velocity shown in Equation (5.14) converges to 0, it represents a successful angle prediction. If it does not converge to 0, return to step (4) and resubstitute the next preset value into the calculation.

$$\begin{cases} \lim\limits_{i \to i_0, j \to j_0} v_Y^{global}(end)|_{(i_0,j_0)} = 0 \\ \lim\limits_{i \to i_0, j \to j_0} v_Z^{global}(end)|_{(i_0,j_0)} = 0 \end{cases} \tag{5.14}$$

(6) Output the angle values with a maximum PSA of (90°-θ_{min}) and a maximum ASA of (180°-θ_{max}).

(7) Calculate the distance in the forward direction further by double integration as in Equation (5.15).

$$D_Z^{global}(end) = \iint_{t_{start}}^{t_{end}} a_Z^{global} \cdot dt \tag{5.15}$$

5.3.4 Applying the CTAA method to 6MWT

Figure 5.6 shows the application of the CTAA method in the 6MWT. From top to bottom, the figure includes the y-axis acceleration data, z-axis acceleration data, the angle between the lower leg and the ground, and the distances of each stride calculated by the CTAA and SAA methods. The red dashed lines indicate the division of gait cycles. The blue asterisks mark the minimum values of y-axis acceleration, which correspond to the maximum PSA, while the green markers indicate the minimum values of z-axis acceleration, corresponding to the maximum ASA.

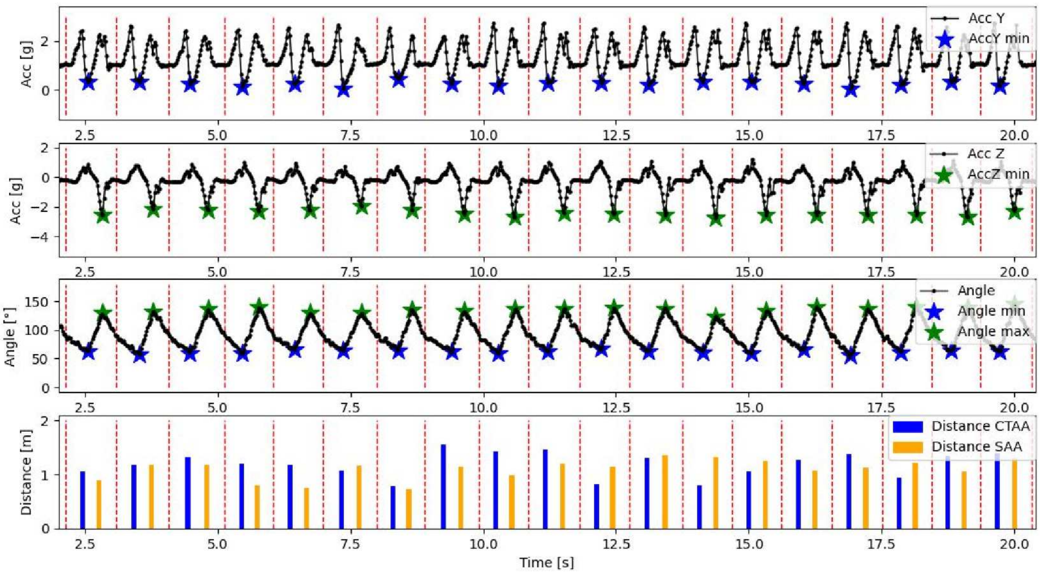


Figure 5.6 Angles and distances obtained by applying the CTAA method to the 6MWT.

5.4 Results

5.4.1 Validation of angle

Figure 5.7 shows the angle changes of three students under three walking conditions: slow, normal, and fast, based on their self-perceived pace. The red curve represents the results calculated by the CTAA method proposed in this study, the blue curve shows the MSA method, and the green curve shows the AFA method. The results indicate that the three methods exhibit similar trends in angle changes throughout the gait cycle, with the CTAA method showing a high degree of consistency with the widely used MSA method. This suggests that although CTAA relies only on acceleration data, it can still accurately estimate lower leg angles during walking. It confirms the effectiveness and practical value of this method without the need for multi-sensor fusion.

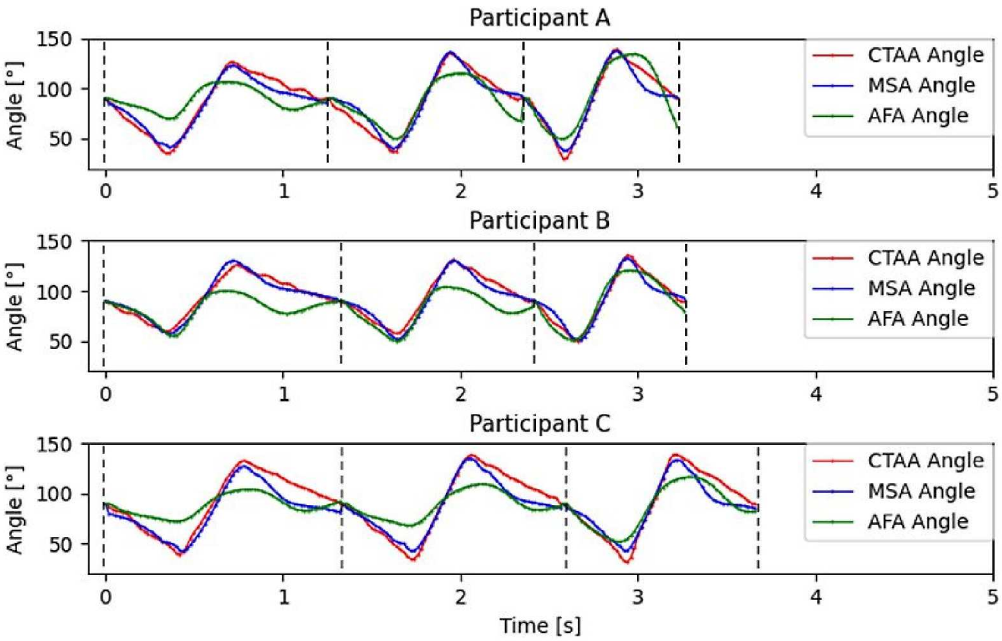


Figure 5.7 Angle changes at three self-perceived walking speeds: slow, normal and fast for 3 students respectively.

Table 5.1 further demonstrates the errors and correlation coefficients of the three methods for angle estimation. The results show that compared to the AFA method, the CTAA method proposed in this study has a smaller error and higher correlation, showing a better angular estimation performance.

Table 5.1 Errors and correlation coefficients of three methods in angle estimation.

Participants (Gender)	Age (years), Height (cm), Weight (kg)	Errors		Pearson r	
		CTAA and MSA	AFA and MSA	CTAA and MSA	AFA and MSA
Student A (M)	27, 172, 65	6.37%	15.28%	0.98	0.84
Student B (M)	30, 181, 66	4.75%	10.38%	0.97	0.88
Student C (M)	26,168,63	9.35%	13.93%	0.97	0.90

5.4.2 Validation of distance

According to the 6MWT guidelines, we extracted data from each 20m straight walking segment and calculated the walking distance using both the CTAA and SAA methods. As shown in the bar chart in Figure 5.8, the comparison between the CTAA method, the SAA method, and the standard distance (20m) is presented. The results show that the distance estimated by the CTAA method is closer to the real value and performs slightly better than the SAA method. This indicates that the CTAA method is feasible for walking distance estimation and further supports that the angle estimation in this method reflects real gait changes.

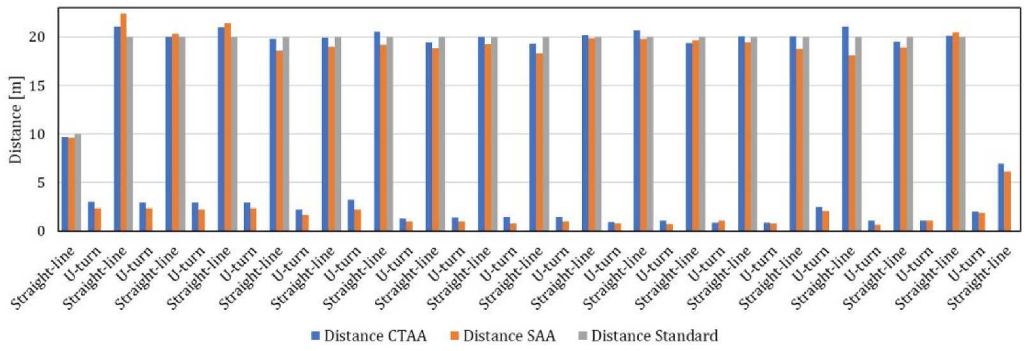


Figure 5.8 Comparison results between CTAA method, SAA method and standard distance (20m).

In addition, we analyzed the walking acceleration data of 6 participants and calculated their walking distances using the CTAA and SAA methods. Table 5.2 shows the total distance during the 6MWT (including U-turn and straight-line walking), and straight-line distance, where the error compared to the 6MWD. The results indicate that for both CTAA and SAA methods, the error between the estimated distance and the 6MWD is within 5%, showing good applicability in everyday walking scenarios. However, it is worth noting that the CTAA method consistently showed lower error compared to the SAA method.

Table 5.2 Information and total distance (U-turn + straight-line) and straight-line distance of the 6 participants.

Participants (Gender)	Age (years), Height (cm), Weight (kg)	Total Distance (m)		Straight-Line Distance (m)			Straight-Line Distance Errors	
		CTAA	SAA	CTAA	SAA	6MWD	CTAA and Doctor	SAA and 6MWD
No.49 (M)	73, 161.0, 44.2	273	262	248	239	250	0.8%	4.4%
No.73 (M)	78, 153.6, 55.2	367	353	324	315	326	0.6%	3.4%
No.57 (M)	78, 159.7, 62.8	392	374	358	348	355	0.8%	2.0%
No.55 (M)	81, 174.5, 77.1	441	423	409	396	414	1.2%	4.3%
No.65 (F)	63, 166.4, 80.8	460	442	416	404	417	0.2%	3.1%
No.70 (M)	57, 172.0, 75.0	582	558	539	518	538	0.2%	3.7%

5.4.3 Cutoff values for gait parameters

In this chapter, we selected acceleration data from 6 participants to analyze their dynamic gait performance during the 6MWT. We mainly extracted the following parameters for each stride: maximum PSA, maximum ASA, distance, and time. We calculated gait velocity (distance/time) and the lower leg swing angle range (maximum ASA - maximum PSA). We set two cut-off values for each gait parameter to assess gait performance.

Firstly, we refer to the two speed cut-off values mentioned in Chapter 2, that is, 1.33 m/s and 1.00 m/s, to assess the gait velocity at each stride. A speed of 1.33 m/s corresponds to a 6MWD greater than 400 meters, which is generally considered to indicate good outdoor mobility and a lower risk of cardiovascular disease [13]. In contrast, a speed of 1.00 m/s corresponds to a 6MWD less than 300 meters and is associated with higher mortality and fall risk [14]; it is also widely used as a diagnostic criterion for frailty and sarcopenia. It should be noted that the 6MWD is not simply the product of speed and time, as the test includes several U-turns, and the 6MWD reflects only the total distance of all straight-line walking parts.

We refer to the walking advice from Japan's "3033 Exercise" report, which suggests replacing normal strides with large strides to strengthen lower limb muscles and increase energy expenditure [23]. According to the report, a normal step length is about 0.37 times a person's height, while a large step is about 0.45 times the height. Based on this standard, we used stride lengths ($\text{Stride length} = 2 \times \text{Step length.}$) equal to $0.74\ (2 \times 0.37)$ and $0.9\ (2 \times 0.45)$ times height as reference values for normal and large stride walking in this study. Furthermore, to link stride length with time, we used a reference speed of 1.33 m/s, commonly associated with good outdoor activity ability, and divided the two stride lengths by this speed to calculate the corresponding stride time reference values. These time values can serve as criteria during actual walking to evaluate whether the walking meets the recommended level for outdoor activity.

Although the two angle parameters, maximum PSA and ASA, reflect the push-off movement of the lower leg and the forward swing of the thigh during walking, we unfortunately did not find reference values for them in the walking process after reviewing many studies. By further analyzing the walking diagram in Figure 5.1, we observed that when the lower leg bends backward, the ankle also dorsiflexes, and when the thigh swings forward, the hip extends. According to the 2022 revision of the joint range of motion and its measurement method by the Japanese Society of Rehabilitation Medicine, the typical dorsiflexion range of the ankle is between 20° or 30°, and the hip extension range is about 125° (125° - 90° = 35°), as shown in Figure 5.9 [24]. Although these angle ranges are obtained from static joint evaluations rather than dynamic walking measurements, they can still serve as reference values for assessing maximum PSA and ASA.

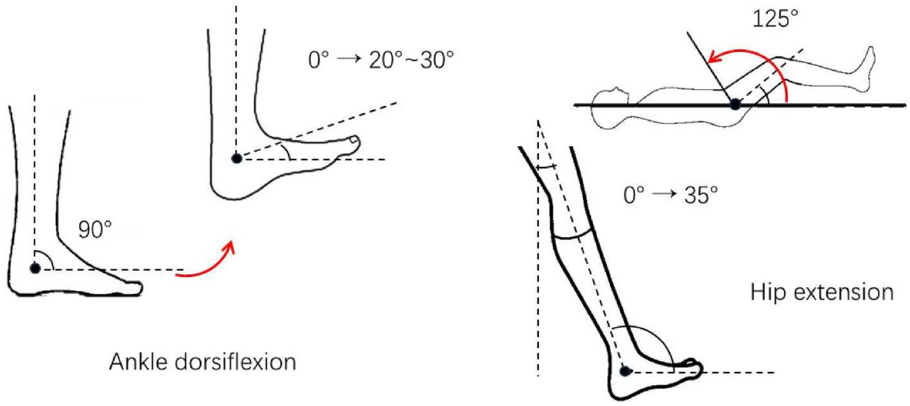


Figure 5.9 Schematic of dorsiflexion of the ankle and extension of the hip joint.

On the other hand, from the illustration in Figure 5.9, it can be observed that when the maximum ASA angle is reached, the body, thigh, and lower leg appear to form a straight line. Using the relationship that normal stride length is approximately 0.74 times the height, and large stride length is about 0.90 times the height, we applied the arctangent function to roughly calculate the corresponding angle, as shown in Equation (5.16). The results show that for normal walking, the reference angle is about 36.5°, which is very close to the hip extension range of 35° (125° - 90° = 35°) described in Figure 5.9.

$$\begin{aligned} \theta &= arctan(0.74) = 36.50° \\ \theta &= arctan(0.90) = 41.98° \end{aligned} \tag{5.16}$$

Given the above results, we define the reference range for the maximum PSA as 20° to 30°, and for the maximum ASA as 35° to 40°. Accordingly, the range of lower leg angle change (ASA - PSA) can be defined as 55° to 70°.

5.4.4 SC-SL gait distribution map

Figure 5.10 shows the SC-SL gait distribution map for 6 older adults. No.49 falls within Range III, which indicates weaker muscle condition with the lowest muscle strength score (WMS1), and was diagnosed with frailty and sarcopenia. No.57 and No.73 are located in Range IV, where slow muscle fibres are weaker; the former has a muscle strength score of WMS2, and the latter WMS1, with a diagnosis of pre-frailty and sarcopenia. No.55, No.65, and No.70 are all located in Range I, which represents normal muscle function, and only No.65 has a muscle strength score of WMS3, while the others all have a WMS4. Notably, the 6MWD of No.55 and No.65 are close to each other, with 414m and 417m, respectively. No.49 has a minimum 6MWD of 250m, while No.70 has a maximum of 538m.In addition, No.57 and No.73 both have 6MWDs between 300m and 400m of 355m and 326m respectively.

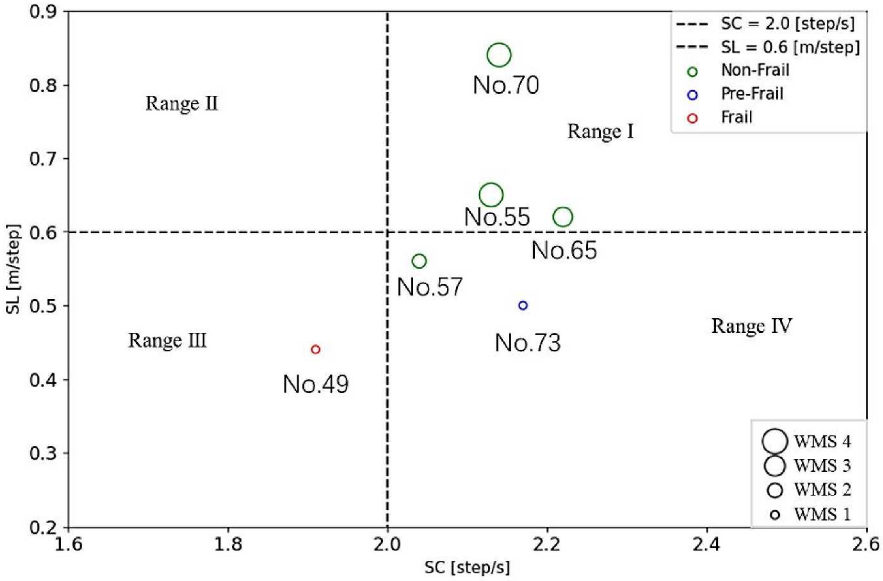
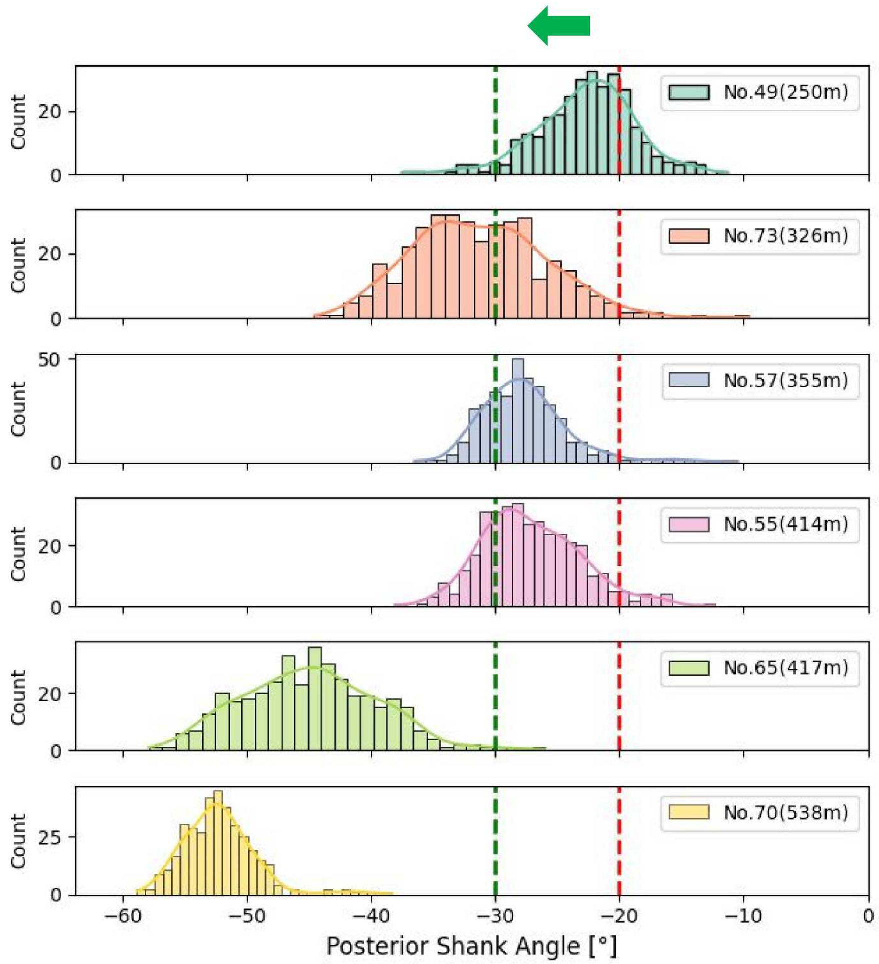


Figure 5.10 SC-SL gait distribution map of 6 older adults.

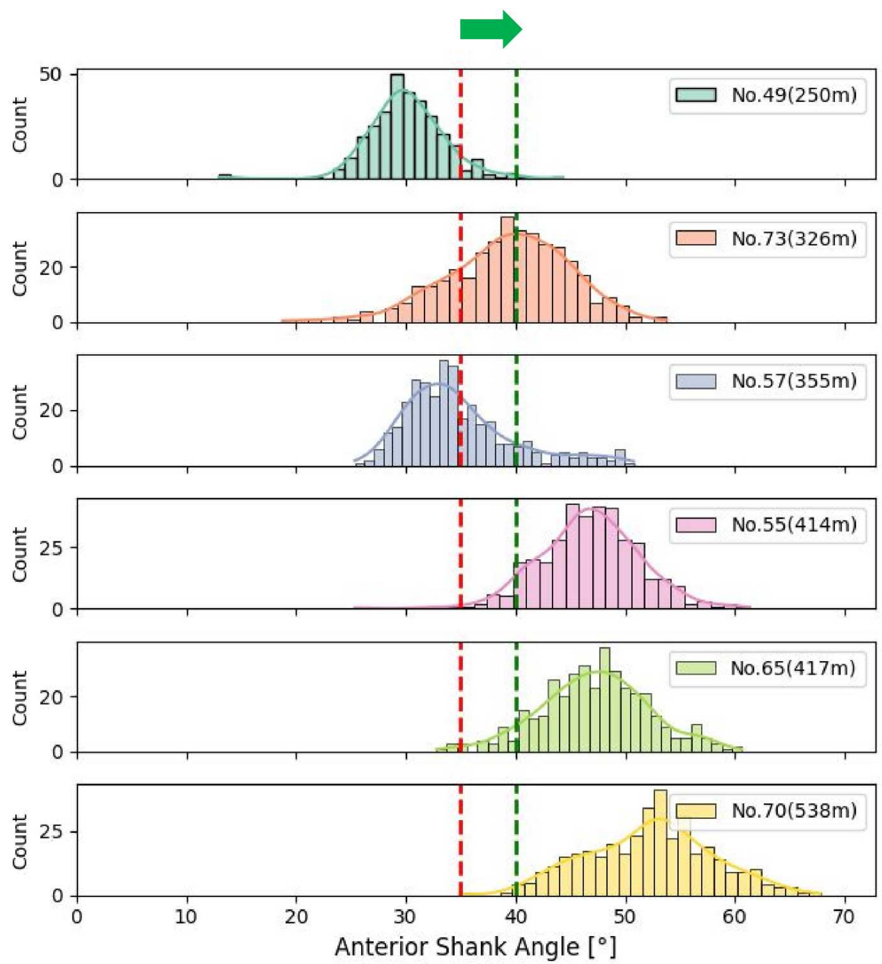
5.4.5 Histograms of gait parameters

Figure 5.11 shows histograms of six gait parameters collected during the 6MWT for six older participants. The parameters include: maximum PSA, maximum ASA, distance, time, angle range, and gait velocity, labeled from Figure 5.11 (a) to Figure 5.11 (f). In the figure, the participants are arranged in ascending order based on their 6MWD. The red and green dashed lines represent the lower and upper reference thresholds for each parameter, respectively: the red line indicates the critical value for weaker gait performance, while the green line marks the reference for stronger gait performance. For example, No.49, who had the lowest 6MWD and was diagnosed with frailty and sarcopenia, had most of their gait parameters below the red line. In contrast, No.70, who had the highest 6MWD, showed most parameters above or near the green line. Additionally, based on the four-level WMS scoring proposed in this study, the six participants, from top to bottom, correspond to WMS1, WMS1, WMS2, WMS4, WMS3, and WMS4. The results showed an overall trend of increasing gait parameters with increasing WMS scores, further validating the good agreement between WMS scores and walking function.

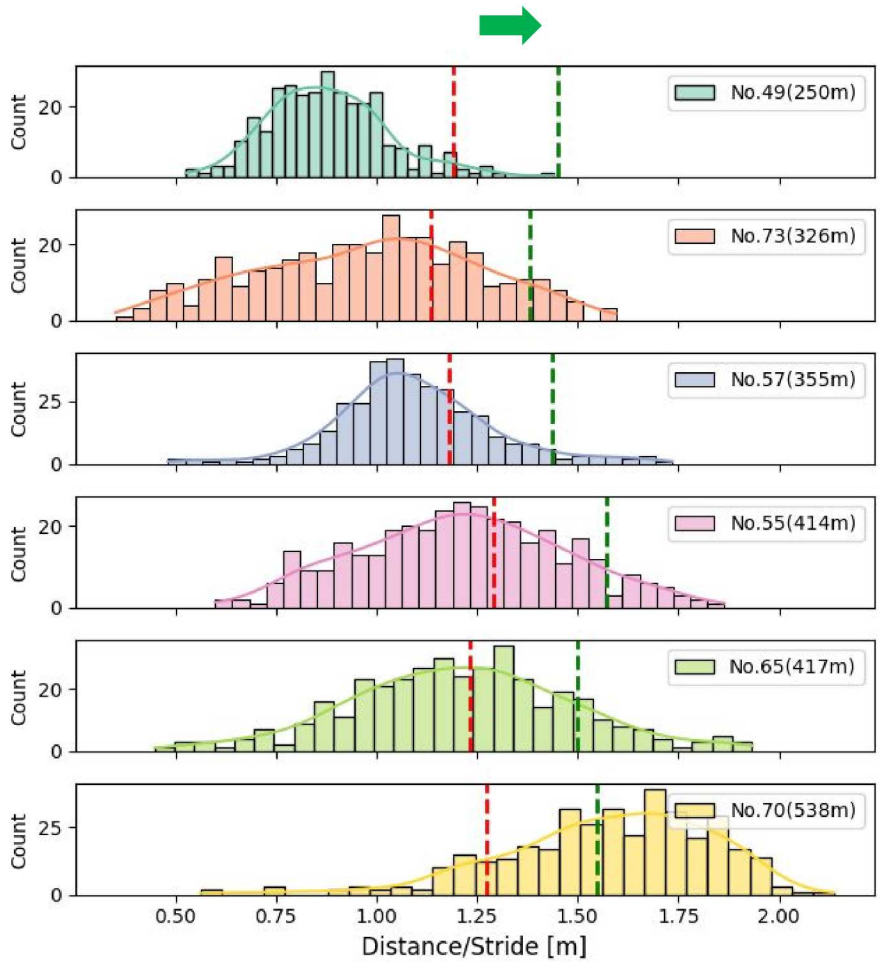
Table 5.3 further summarizes the gait performance of six participants during the 6MWT by calculating the percentage of each stride that fall below the lower reference value (red line), above the upper reference value (green line), and within the range between them for six gait parameters. Taking No.73 as an example, although diagnosed with sarcopenia, most of their PSA, ASA, and time were within the reference range, with only the distance falling below the lower limit. Notably, about 7.2% of this participant's distances were classified as large, and 22.4% were in the transition zone between normal and large.


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Posterior Shank Angle [°]

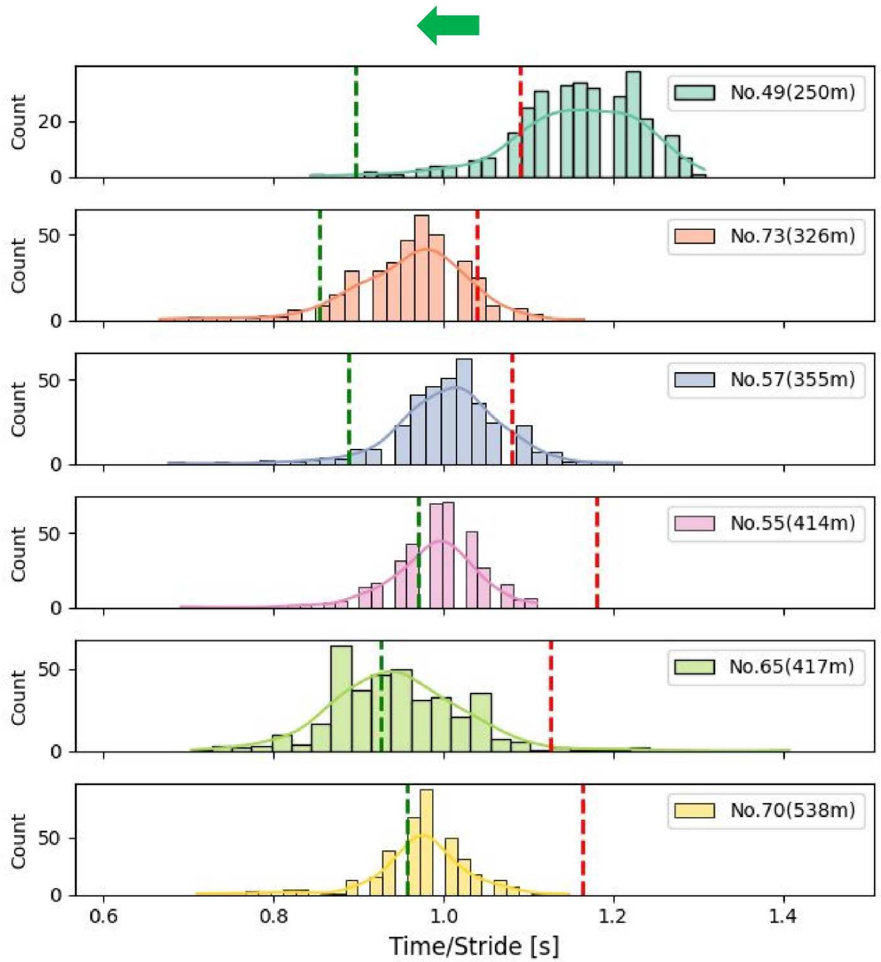
(a)


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Anterior Shank Angle [°]

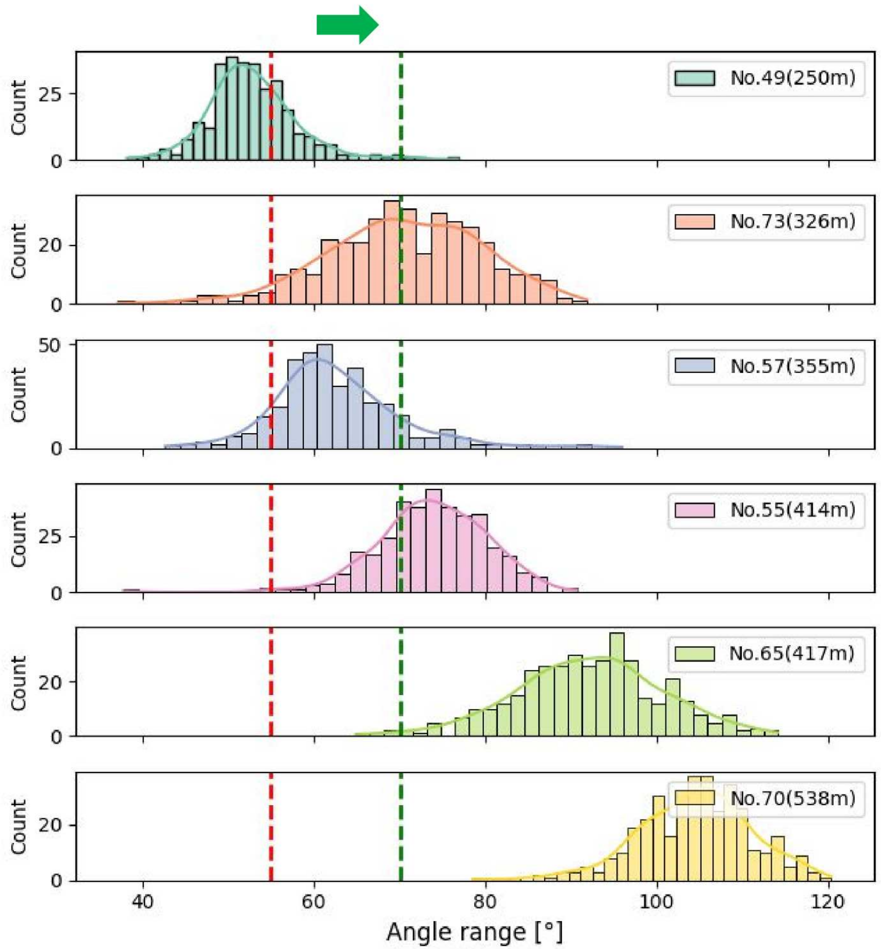
(b)


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Distance/Stride [m]

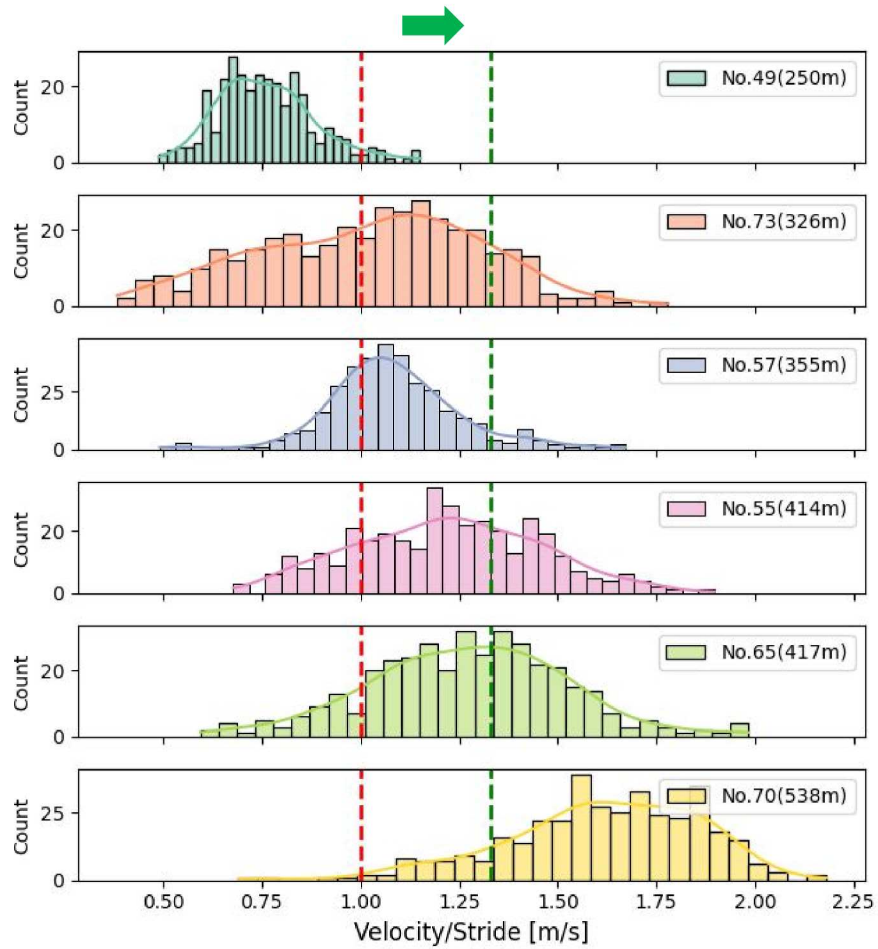
(c)


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Time/Stride [s]

(d)


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Angle range [°]

(e)


No.49(250m)
No.73(326m)
No.57(355m)
No.55(414m)
No.65(417m)
No.70(538m)
Count
Velocity/Stride [m/s]

(f)

Figure 5.11 shows histograms of six gait parameter distributions for six older participants. Figures (a) to (f) represent maximum PSA, maximum ASA, distance, time, angle range, and gait velocity, respectively. From top to bottom, the lower limb muscle strength levels are WMS1, WMS1, WMS2, WMS4, WMS3, and WMS4, with 6MWD gradually increasing at 250m, 326m, 355m, 414m, 417m, and 538m. The red line represents the lower reference limit for each gait parameter, while the green line marks the upper threshold.

Table 5.3 Percentage and number of each parameter falling below the lower reference limit (red line), above the upper reference limit (green line), and within the range between them of six participants.

Participants (Total strides)	Posterior Shank Angle						Anterior Shank Angle					
	|Angle|≥30°		20°≤|Angle|<30°		|Angle|<20°		Angle≥40°		35°≤Angle<40°		Angle<35°	
No.49 (311)	3.5%	11	73.3%	228	23.2%	72	0.6%	2	6.1%	19	93.2%	290
No.73 (375)	59.5%	223	38.4%	144	2.1%	8	47.2%	177	32.0%	120	20.8%	78
No.57 (358)	23.7%	85	73.5%	263	2.8%	10	14.5%	52	23.2%	83	62.3%	223
No.55 (364)	23.4%	85	71.4%	260	5.2%	19	94.5%	344	4.7%	17	0.8%	3
No.65 (380)	99.2%	377	0.8%	3	-	-	93.2%	354	5.8%	22	1.1%	4
No.70 (370)	100%	370	-	-	-	-	99.5%	368	0.5%	2	-	-
Participants (Total strides)	**Distance (*H: Height)**						**Time (*v=1.33m/s)**					
	D≥0.45H		0.37H≤D<0.45H		D<0.37H		T≥0.45H/v		0.37H/v≤T<0.45H/v		T<0.37H/v	
No.49 (311)	-	-	3.5%	11	96.5%	300	85.5%	266	14.2%	44	0.3%	1
No.73 (375)	7.2%	27	22.4%	84	70.4%	264	12.2%	46	80.3%	301	7.5%	28
No.57 (358)	5.3%	19	22.3%	80	72.4%	259	11.5%	41	84.6%	303	3.9%	14
No.55 (364)	7.7%	28	29.9%	109	62.4%	227	-	-	67.6%	246	32.4%	118
No.65 (380)	14.2%	54	32.6%	124	53.2%	202	2.4%	9	60.5%	230	37.1%	141
No.70 (370)	57.3%	212	29.2%	108	13.5%	50	-	-	76.8%	284	23.2%	86
Participants (Total strides)	**Angle range**						**Velocity**					
	Range≥70°		55°≤Range<70°		Range<55°		v≥1.33m/s		1.00≤v<1.33m/s		v<1.00m/s	
No.49 (311)	1.3%	4	27.0%	84	71.7%	223	-	-	4.5%	14	95.5%	297
No.73 (375)	52.5%	197	42.9%	161	4.5%	17	12.8%	48	44.3%	166	42.9%	161
No.57 (358)	13.7%	49	76.3%	273	10.0%	36	7.3%	26	64.8%	232	27.9%	100
No.55 (364)	75.5%	275	23.9%	87	0.6%	2	32.4%	118	47.8%	174	19.7%	72
No.65 (380)	98.9%	376	1.1%	4	-	-	42.1%	160	45.3%	172	12.6%	48
No.70 (370)	100%	370	-	-	-	-	87.8%	325	11.1%	41	1.1%	4

5.5 Discussion

To further improve the assessment of muscle function and gait performance in older adults during 6MWT, and to provide practical guidance with numerical values for clinical rehabilitation and walking interventions, this chapter proposes a histogram-based analysis method using upper and lower reference values for gait parameters. By comparing gait indicators from the 6MWT, such as maximum PSA, maximum ASA, distance, time, gait velocity, and angle range, with reference values derived from literature or theoretical derivation, this method enables visual presentation of walking quality and provides scientific and quantitative support for rehabilitation, personalized walking plans, and health monitoring. This approach helps in identifying individuals with potential low limb muscle weakness at an earlier stage, and helps clinicians to guide them in optimizing their gait patterns to achieve the rehabilitation goal.

In addition, this chapter develops a new algorithm called CTAA using acceleration data to calculate gait parameters, which addresses the limitations of the traditional 6MWT that relies on a fixed site and lacks dynamic parameter assessment. Without relying on multiple sensors, the CTAA method estimates lower leg angles and walking distances by analyzing gait patterns and walking kinematics. Table 5.1 shows that the angle estimation error of CTAA is lower than that of AFA and closely matches results from mainstream methods like MSA. Furthermore, Table 5.2 indicates that the distance estimation by CTAA has a smaller relative error than the SAA method and is closer to the standard 20m straight-line distance in the 6MWT. These results confirm the accuracy and practicality of the proposed method, especially for gait analysis studies and applications that only collect acceleration data.

To evaluate the gait quality of each stride more scientifically and systematically, this chapter introduces several representative reference values as the basis for classifying and assessing walking performance. Specifically, gait velocity reference values are set at 1.00 m/s and 1.33 m/s, which correspond to diagnostic criteria for frailty and sarcopenia, as well as cut-off points indicating high fall risk and good outdoor activity ability. Distance references are based on the "3033 Movement" report [23], which suggests that taking large strides helps strengthen lower limb muscles. According to this report, a normal stride length is 0.74 times a person's height, and a large stride is 0.90 times the height. Time references are calculated by dividing the above stride distances by 1.33 m/s, reflecting the expected time for healthy outdoor activity. Angle references are taken from the Japanese Association of Rehabilitation Medicine's guidelines on joint range of motion [24], using an ankle dorsiflexion range of 20~30° as the reference for maximum PSA, and 35° as the lower limit for maximum ASA based on hip extension. Additionally, an upper limit of 40° for ASA is estimated using the arctangent function based on the large stride-to-height ratio. Combining these values, the angle range of lower leg change (ASA–PSA) is set between 55° and 70°. These reference values not only provide a quantitative standard for gait distribution but also help shift gait assessment from subjective descriptions to objective judgment, offering a more reliable basis for detecting abnormal gait patterns and a convenient way for physicians to judge the effectiveness of intervention.

Figure 5.11 presents histograms showing the distribution of six gait parameters during the 6MWT for six older participants. This visual representation clearly illustrates the overall gait quality of each individual. Red and green lines indicate the reference ranges for weaker and stronger performance, respectively, allowing for quick identification of gait patterns and potential intervention needs. The figure highlights the extent to which each subject deviates from gait metrics and serves as a quantitative tool for identifying individuals with "gait disadvantaged" in rehabilitation and health monitoring. Compared to the traditional 6MWD, which only measures total walking distance, this method provides a more comprehensive view of dynamic gait performance and underlying deficits. By comparing participants' gait parameters that lie at the lower and upper limits of a reference threshold, clinicians and researchers can determine which parameters fall within optimal ranges and which require targeted intervention.

Additionally, Figure 5.10 shows that the methods introduced in Chapters 3 and 4 were applied to evaluate lower limb muscle condition and quantify muscle strength for the six participants. For example, No.49 and No.70 represent the weakest and strongest gait profiles, respectively, appearing in Range III and Range I of the SC-SL gait distribution map. Their corresponding WMS scores were WMS1 and WMS4. The results show that the weaker participant (No.49) had most gait parameters below the red line, indicating clear signs of gait decline, while the stronger participant (No.70) had values mostly above or near the green line, reflecting good muscle function.

Table 5.3 further summarizes the percentage of gait parameters for each of the six participants that fall within the upper and lower reference thresholds. This ratio-based analysis not only reveals how often each subject demonstrated effective walking during the 6MWT, but also supports the development of more tailored walking suggestions. For example, No.73 was diagnosed with sarcopenia, 7.2% of their strides qualified as large, and 22.4% fell between normal and large stride distance, indicating that their muscle status still had some potential for recovery. For such individuals, it is recommended to prioritize maintaining a normal or slightly large stride during walking, rather than focusing on increasing walking speed. This type of gait training may help preserve or gradually improve lower limb muscle capacity. In contrast, No.49 showed most gait parameters below the reference thresholds, which may reflect common gait problems in many older adults. From a clinical rehabilitation perspective, if histogram patterns for gait parameters show a peaked change or an overall shift to the more favourable side after a period of walking intervention, this can be regarded as a meaningful indicator of successful rehabilitation and holds significant clinical value.

In addition, we observed that No.55 and No.65 had very similar 6MWD values (414 m and 417 m, respectively). According to Table 5.3, the distance and gait velocity per stride were also roughly the same between the two. However, there were differences in time and maximum PSA, where No.65 showed better performance than No.55. Based on the basic body information in Table 5.2, No.65 is shorter than No.55. To achieve a similar walking distance and speed, No.65 inevitably needed to increase their PSA angle and swing their lower leg more frequently, resulting in a shorter time. Although No.65 appeared more active in gait performance, their WMS score was WMS3, slightly lower than No.55's WMS4. This result is mainly due to No.65's younger age and shorter height, which led to lower energy expenditure during the 6MWT. As a result, the calculated muscle strength level was slightly lower than that of No.55.

In summary, this method reveals the gait distribution characteristics of older adults under different muscle capacity and further confirms the effectiveness of the histogram-based analysis using reference values in identifying individual differences. This provides theoretical support for doctors to develop more targeted training guidance. Especially during rehabilitation, continuously tracking the proportion of various gait parameters within the reference ranges allows for dynamic evaluation of training effectiveness and offers a reliable basis for adjusting and optimizing gait intervention plans.

5.6 Conclusion

This chapter focuses on the assessment and intervention strategies for walking ability in older adults. It proposes and validates a histogram-based analysis method using gait reference values, along with a new algorithm called CTAA, to overcome the limitations of traditional 6MWT in evaluating dynamic gait quality. By introducing theoretical and literature-based reference values for key indicators such as maximum PSA, ASA, distance, time, gait velocity, and angular range, the method enables a visual and quantitative analysis of gait performance. Using a dual-reference comparison approach, the gait distribution characteristics of six older participants were systematically analyzed, revealing differences in performance based on lower limb muscle capacity and offering targeted rehabilitation and walking suggestions. Moreover, the CTAA algorithm can accurately estimate leg angles and stride distances without relying on multiple sensors, enhancing the clinical applicability of 6MWT. The analysis method developed in this study improves the ability to assess gait and muscle status in older adults, supports the quantitative setting of rehabilitation goals and personalized training plans. It holds great potential for future use in home health monitoring and smart rehabilitation applications.

References

[1] Galloway M T, Jokl P. Aging successfully: the importance of physical activity in maintaining health and function[J]. JAAOS-Journal of the American Academy of Orthopaedic Surgeons, 2000, 8(1): 37-44.

[2] McPhee J S, French D P, Jackson D, et al. Physical activity in older age: perspectives for healthy ageing and frailty[J]. Biogerontology, 2016, 17: 567-580.

[3] Eckstrom E, Neukam S, Kalin L, et al. Physical activity and healthy aging[J]. Clinics in geriatric medicine, 2020, 36(4): 671-683.

[4] Chen N, He X, Feng Y, et al. Effects of resistance training in healthy older people with sarcopenia: a systematic review and meta-analysis of randomized controlled trials[J]. European Review of Aging and Physical Activity, 2021, 18: 1-19.

[5] Hämäläinen O, Tirkkonen A, Savikangas T, et al. Low physical activity is a risk factor for sarcopenia: a cross-sectional analysis of two exercise trials on community-dwelling older adults[J]. BMC geriatrics, 2024, 24(1): 212.

[6] Wang Y, Lu Y, Fang Z, et al. Brisk walking improves motor function and lower limb muscle strength in Chinese women aged 80 years and older[J]. Scientific Reports, 2024, 14(1): 7933.

[7] Liang S, Xu J, Zhao G. An investigation into the bilateral functional differences of the lower limb muscles in standing and walking[J]. PeerJ, 2016, 4: e2315.

[8] Lim Y P, Lin Y C, Pandy M G. Lower-limb muscle function in healthy young and older adults across a range of walking speeds[J]. Gait & Posture, 2022, 94: 124-130.

[9] Ferté J B, Boyer F C, Taiar R, et al. Impact of resistance training on the 6-minute walk test in individuals with chronic obstructive pulmonary disease: a systematic review and meta-analysis[J]. Annals of Physical and Rehabilitation Medicine, 2022, 65(3): 101582.

[10] Spruit M A, Polkey M I, Celli B, et al. Predicting outcomes from 6-minute walk distance in chronic obstructive pulmonary disease[J]. Journal of the American Medical Directors Association, 2012, 13(3): 291-297.

[11] Morales-Blanhir J E, Palafox Vidal C D, Rosas Romero M J, et al. Six-minute walk test: a valuable tool for assessing pulmonary impairment[J]. Jornal brasileiro de pneumologia, 2011, 37: 110-117.

[12] Savarese G, Paolillo S, Costanzo P, et al. Do changes of 6-minute walk distance predict clinical events in patients with pulmonary arterial hypertension? A meta-analysis of 22 randomized trials[J]. Journal of the American College of Cardiology, 2012, 60(13): 1192-1201.

[13] Newman A B, Simonsick E M, Naydeck B L, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability[J]. Jama, 2006, 295(17): 2018-2026.

[14] Demir R, Küçükoğlu M S. Six-minute walk test in pulmonary arterial hypertension[J]. Anatolian journal of cardiology, 2015, 15(3): 249.

[15] Combs S A, Van Puymbroeck M, Altenburger P A, et al. Is walking faster or walking farther more important to persons with chronic stroke?[J]. Disability and rehabilitation, 2013, 35(10): 860-867.

[16] Moissenet F, Leboeuf F, Armand S. Lower limb sagittal gait kinematics can be predicted based on walking speed, gender, age and BMI[J]. Scientific reports, 2019, 9(1): 9510.

[17] Muro-De-La-Herran A, Garcia-Zapirain B, Mendez-Zorrilla A. Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications[J]. Sensors, 2014, 14(2): 3362-3394.

[18] Najafi B, Khan T, Wrobel J. Laboratory in a box: wearable sensors and its advantages for gait analysis[C]//2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2011: 6507-6510.

[19] ATS. Committee on Proficiency Standards for Clinical Pulmonary Function Laboratories, ATS Statement[J]. American Journal of Respiratory and Critical Care Medicine, 2002, 166(1): 111-117.

[20] Liu F T, Wang Y T, Ma H P. Gesture recognition with wearable 9-axis sensors[C]//2017 IEEE International Conference on Communications (ICC). IEEE, 2017: 1-6.

[21] Macias E, Torres D, Ravindran S. Nine-axis sensor fusion using the direction cosine matrix algorithm on the msp430f5xx family[J]. Application Report, 2012.

[22] Trentzsch K, Melzer B, Stölzer-Hutsch H, et al. Automated analysis of the two-minute walk test in clinical practice using accelerometer data[J]. Brain Sciences, 2021, 11(11): 1507.

[23] イキイキ!!大また歩き（3033 運動）：https://www.pref.kanagawa.jp/docs/ui6/3/3033/try/walk.html, (accessed on 28 April 2025).

[24] 関節可動域表示ならびに測定法改訂について: https://www.jsmr.org/documents/range_of_motion.pdf, (accessed on 30 April 2025).

Chapter 6 Conclusions and Future Works

6.1 Conclusions

With the global aging population continuing to grow, problems caused by declining muscle function, such as frailty, sarcopenia, increased fall risk, and reduced quality of life, have become increasingly serious. This study aims to early detect lower limb muscle weakness in elderly individuals by constructing a wearable sensor system that automatically collects walking data from the widely used 6-minute walk test (6MWT) in clinical practice, developing methods for analysing walking data, and establishing evaluation indicators for lower limb muscle strength.

First, an automated 6MWT data collection system using a three-axis accelerometer was constructed that is capable of measuring in various environments, and an algorithm was also established to extract basic walking function indicators from the 6MWT data, such as average gait velocity (GV), step length (SL), step cadence (SC), and 6-minute walking distance (6MWD).

Second, a clinical study was conducted on 60 elderly subjects with frailty diagnosis based on the J-CHS criteria and the 6MWT test. A new method for determining frailty using only 6MWT data was proposed by analyzing the relationships between the basic indicators extracted from the 6MWT and the indexes in the J-CHS criteria, and its effectiveness was validated through comparison with clinical diagnosis results.

Furthermore, the relationship between 6MWT data and 6-minute walk energy expenditure (6MWEE) was analyzed, and a new index called WMS was proposed to assess walking muscle strength in four levels. The validity of this WMS indicator was also confirmed through comparison with the diagnostic results based on the J-CHS criteria and AWGS criteria.

Finally, an algorithm was developed to accurately calculate the lower leg swing angle and the distance of each stride based on walking (6MWT) data, with the aim of providing objective gait analysis data to promote safe and efficient walking. This algorithm is not only applicable to the 6MWT but also to everyday walking, allowing for accurate estimation of 6MWD even in environments where straight-line distance measurement is difficult. Additionally, the algorithm captures individual gait changes and presents a method for visualizing walking status to help physicians guide walking in the elderly.

6.2 Future Works

In the future, the WMS index and gait analysis method developed in this study hold the potential to lead to the development of a multidimensional health assessment model that relies solely on objective walking performance during daily activities, potentially replacing existing criteria for evaluating frailty and sarcopenia (such as the J-CHS and AWGS criteria). Achieving this goal will require further large-scale data collection and analysis to improve the accuracy and generalisability of the WMS index and gait analysis method.

Moreover, the method proposed in this study suggests the possibility of complementing the objective evaluation of treatment effects in cardiopulmonary-related diseases, as well as visualising the impact of rehabilitation and training on maintaining and improving muscle condition in the elderly, with further research and development in these application areas strongly encouraged in future work.

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