A Novel Environment-Adaptive Timed Up and Go Test System for Fall Risk Assessment With Wearable Inertial Sensors

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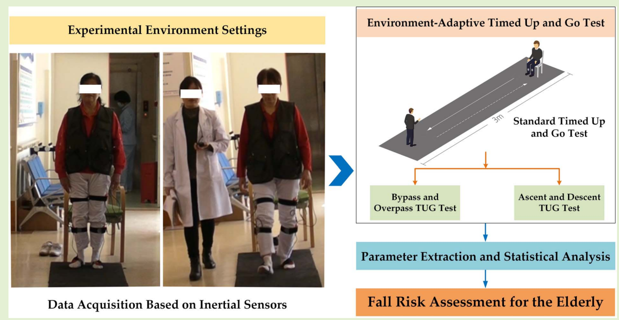
***Abstract*—Objective: Falls are often accompanied by huge social costs, and fall risk assessment is essential to protect the elderly from serious injuries and reduce financial burdens. The standard timed up and go (TUG) balance assessment test focuses on the total walking time and scenarios without environmental changes, which is flawed in providing rich information related to falls and evaluating the gait adaptability in response to environmental changes. Therefore, a fall risk assessment system that relies on a variable environment is actually needed. Methods: We have constructed an environment-adaptive TUG (EATUG) test system with three terrain surfaces (levels/obstacles/stairs). One hundred and three elderly from Shenzhen Luohu Hospital is recruited to participate in the experiment. The wearable inertial sensors attached to the two shanks are used to acquire data, and the gait parameters that may be related to falls are extracted and quantified. Results: Most of the parameters have significant differences between the high-risk group and the low-risk group (e.g., peak power, maximum radius, double support, etc., p < 0.001). In addition, the average sensitivity and specificity of fall risk prediction are 85.7% and 92.9%, while the average accuracy is 9.52% higher than the standard TUG test. Conclusion: The EATUG test system can provide richer gait characteristics and fall-related information, which is a good improvement on the drawbacks of the standard TUG test. Significance: The proposed test system is expected to replace the standard TUG test and be used for fall screening of high-risk elderly in the community to reduce the occurrence of falls.**



***Index Terms*—Falls risk assessment, timed up and go (TUG) test, the elderly, wearable inertial sensors, environment-adaptive TUG (EATUG) test.**

I. Introduction

According to the World Population Prospects (WPP) 2019 report, the elderly population over 65 years old accounts for 9% of the global population, by 2050, one in six people in the world will be over age 65 (16%). Besides, the number of persons aged 80 years or over is projected to triple, from 143 million in 2019 to 426 million in 2050 [1]. With the aging of the population, falls have become a major safety problem for the elderly, adults older than 65 years of age suffer the greatest number of fatal falls. According to World Health Organization (WHO) statistics, approximately 37.3 million falls need to be treated every year, which is the second leading cause of unintentional injuries after road traffic injuries [2]. The financial costs associated with fall-related injuries are substantial. For example, the American Centers for Disease Control and Prevention (CDC) report that every year about $50 billion is spent on medical costs related to non-fatal fall injuries, and $754 million is spent related to fatal falls [3].

Studies have shown that targeted interventions (e.g., sports training) can prevent falls [4], [5]. Therefore, it is of great significance to assess the risk of falls in the elderly. Through the fall risk assessment, the elderly with high fall risk can be screened out, and intervention measures can be taken on them to improve their gait stability. Commonly used clinical

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gait and balance tests include the Timed Up and Go (TUG) test, the Tinetti Balance Assessment, and the Berg Balance Scale (BBS) [6]–[8], etc. The TUG test is quick, requires no special equipment or training, and is easily included as part of the routine medical examination. Given the above advantages, the TUG test is widely used for gait and fall risk assessment and is recommended by the American Geriatrics Society (AGS) and the British Geriatric Society (BGS) [9]. It has been found that the time parameter of the TUG test is related to the risk of falling [10]. However, the standard TUG test simply depends on the total time, ignoring the value of other gait characteristics, and is not yet sufficient to fully assess the risk of falls, as criticized in many studies [11]–[14].

Besides, the standard TUG test focuses on walking in horizontal terrain, which is not sufficient to evaluate the gait adaptability of the elderly in complex environments [10]. The elderly living in the community usually need to adjust their gait in response to changes on the trail, which is strongly related to falls [15], [16]. For example, it is necessary to avoid obstacles that suddenly appear on the sidewalk, and the changes in gait parameters at this time can reflect the ability of gait balance control. Compared with individual general fall risk factors (i.e., subject characteristics, clinical gait and balance testing, quantitative gait assessment), the assessment of gait adaptability for terrain changes can improve the classification of expected falls [17]. Therefore, there is an urgent need for a walking balanced assessment system that relies on a variable environment and multiple parameters.

External factors such as obstacles and slopes can effectively reflect the gait adaptability of the elderly and promote fall risk assessment [18] [19]. Wang *et al.* use the performance to predict the risk of falling for the elderly, i.e., the behavior in the process of crossing the stairs [20], [21]. It is of great significance to establish the research on the activities of the elderly on the stairs [22]. Secondly, obstacles are also used to measure gait adaptability. The related gait test has found that the adjustment ability of the elderly in encountering obstacles is worse than that of the young [23], [24]. Besides, although the TUG test has flaws, it involves representative movements in our daily lives (e.g., standing, walking, turning, and sitting) and does not require complicated instructions, the advantages are worth retaining [25]. In summary, we designed experiments based on three different terrain surfaces (levels/obstacles/stairs) and evaluated the adjustment of gait parameters with environmental changes.

This research mainly focuses on three objectives: (1) Establish a fall risk assessment system for the elderly that simulates the community environment, which can involve terrain changes, provide rich gait characteristics and information related to falls, and have a higher fall risk prediction performance; (2) Compare the significant differences of the gait spatiotemporal parameters of the elderly with high fall risk and low fall risk under different TUG tests; (3) Estimate the influence of variability terrain on the gait parameters to explore the gait adaptability of the elderly. In general, we hope this work can provide comprehensive guidance for fall risk assessment of the elderly in the community, improve the accuracy of high-risk screening, formulate intervention strategies and ultimately reduce the occurrence of falls.

The rest of this paper is organized as follows: Section II describes the experimental setup and data collection in detail. Section III shows the data processing and feature extraction process. Then, the results of the significance analysis in different aspects are given in Section IV. Section V analyzes and discusses the contribution and limitations of this research. Finally, Section VI summarizes the work and looks forward to future tasks.

II. Experimental Setup and Data Collection

A. Participants

One hundred and three elderly (24 male and 79 female) from the Luohu District Medical and Nursing Integrated Geriatric Hospital of Shenzhen are recruited as experimental subjects. All subjects live in the community, and the inclusion criteria are as follows: (1) The elderly are over 60 years old; (2) The elderly can use a walker or walk independently; (3) The elderly do not have severe osteoporosis; (4) The elderly have a normal cognitive function (Montreal Cognitive Assessment score $\geq$23 [26]) and are not accompanied severe neurodegenerative diseases; (5) The elderly can complete all questionnaires and experimental tests. Before the experiment, participants are required to sign an informed consent form, and all experiments involving human subjects have been approved by the relevant institutional review board.

To divide the elderly into high-risk and low-risk groups, the questionnaires and the berg balance scale (BBS) are used. Participants are first asked to fill the questionnaire, which included the following aspects: (1) Personal information (age, height, etc.); (2) History of falls within the past year; (3) History of diseases (high blood pressure, diabetes, etc.); (4) History of medications (sleeping pills, psychotic agents, etc.); (5) Living conditions (regular exercise, use crutches, etc.); (6) Psychological factors such as fear of falling. Subsequently, static and dynamic balance BBS tests are performed on the elderly. Considering the fall history and BBS score, the criteria for the classification of fall risk are determined [27]–[29]. The elderly who has experienced multiple falls ($n \geq 2$) in the past year will be direct as a "high-risk group" because it is likely to be caused by a physical disorder [22]. Besides, the elderly experienced one fall ($n = 1$) and BBS score ≤ 45, no fall ($n = 0$) but BBS score $\leq$42 were assigned to the high-risk group, while the others were assigned to the low-risk group (Fig. 1). All the operation is performed by a professional physical therapist. Finally, the high-risk and low-risk groups are assigned 32 and 71 subjects. Cohort characteristics are shown in Table I.

B. Environment-Adapting TUG Test System

Studies have shown that the gait adaptability of the elderly is related to the environment, and about 31% of falls are caused by environmental changes [30]. Ferraro *et al.* demonstrate that when walking on a sloping surface, the step length, mean cadence, and mean normalized velocity of elderly people are significantly reduced [19]. Caetano *et al.* evaluate the response of gait adaptability changes to obstacles or stepping targets

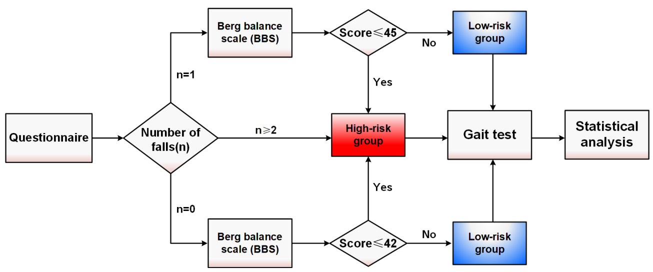

Fig. 1. The flow chart of the classification of the elderly into high-risk and low-risk groups.

TABLE I
DEMOGRAPHIC CHARACTERISTICS OF OLDER PARTICIPANTS

Cohort Information	Mean ± Standard Deviation		
	High-risk (32)	Low-risk (71)	p-value
Gender[F|M]	[23|9]	[56|15]	0.124 ‡
Age[years]	**81.9 ± 8.47**	**75.2 ± 6.95**	**$p < 0.001$**∗∗∗†
Height[cm]	157.6 ± 9.57	157.3 ± 7.35	0.838 †
Weight[kg]	58.8 ± 11.6	59.1 ± 11.5	0.742 †

†: Mann-Whitney U test; ‡: Fisher's exact test. Key: ∗$p<0.05$; ∗∗$p<0.01$; ∗∗∗$p<0.001$. Results in bold are found to provide significant discrimination between the two groups.

and find that the gait characteristics of the elderly show slow, short, and multiple steps with longer time in double support [31]. Therefore, studying gait adjustment strategies when encountering obstacles or stairs can provide more information related to the risk of falling. We designed an environment-adaptive TUG (EATUG) test system based on the community environment, which consists of three different terrain tests, describe as follows.

1) Standard TUG Test: Participants are asked to stand up from the chair, walk 3 m on flat ground at a comfortable pace, then turn around, return to the chair, and sit down [32]. The standard TUG test is shown in Fig. 2 (a).

2) Bypass and Overpass TUG Test: Participants should stand up from the chair, walk 1.5 m and overpass an obstacle (10 cm high and 15 cm wide), turn around after walking 3 m, and bypass the obstacle when returning, as shown in Fig. 2 (b).

3) Ascent and Descent TUG Test: Participants should stairs ascent first, walk through a 0.8 m flat terrace, then descend the stairs, and return at 3 m, as shown in Fig. 2 (c). The height and width of each staircase are 15 cm and 20 cm.

C. Data Collection

The data is measured by two inertial sensors attached to the left and right shanks (about 15 cm below the knee joint). The sensor node consists of an STM32F407 microcontroller (STMicro electronics, Geneva, Switzerland), an MPU9250 accelerometer and gyroscope module (TDK InvenSense, San Jose, CA, USA), an Arduino Bluetooth module, and a lithium battery (300 mAh). The circuit board integrating each module is installed in a small casing, and the size of each node is $56.5 \times 37.5 \times 15.5$ mm^3, weighs about 30 g, and the sampling frequency is 60 Hz. The range of accelerometer and gyroscope is ±8g and ±1000°/s, respectively. Finally, the two inertial sensors are connected by wires and can be used for synchronous data collection through interrupt trigger signals.

Before data acquisition, the elderly will be instructed and trained to promote better execution of the test. During the experiment, the elderly was allowed to use walking aids, and each TUG test would be performed at least twice, with a five-minute rest between two tests. Throughout the environment-adaptive TUG tests, the two sensors are kept on the sagittal plane of the shank, and video tracking is used as a reference. The motion capture is through a high-definition infrared camera (Micro Star Electronic Technology Co. Ltd, Shenzhen, China) with a capture frequency of 30 Hz.

III. METHOD

A. Preprocessing

Before parameter estimation, the raw accelerometer and gyroscope data need to be pre-processed. For acceleration signals, the detrend function is used to process all signals to remove the influence of static gravity components and other low-frequency trends [22]. For the gyroscope signal, the skewness of the signal needs to be calculated for each walk to measure the asymmetry of the signal. If the skewness of the signal is less than zero, the gyroscope signal will be automatically inverted in the software to ensure the correct polarity of the signal [33]. Before further processing, the zero-phase 5th order Butterworth filter with a 5-Hz corner frequency is used to filter the signal after skew correction and trend removal. All operations are performed on MATLAB R2019a.

B. Gait Parameter Extraction

The clinical practice guidelines of AGS and BGS to prevent falls provide the main risk factors associated with falls in the elderly [9]. Many of the self-reported factors discussed in the guideline are used to create logistic regression models to predict the risk of falling [10]. Besides, some currently reported studies use quantitative TUG test parameters to evaluate the risk of falls, which provides a reference for feature extraction of gait parameters [22] [34]. Our purpose is to extract the features based on the sensor data of the anterior-posterior (AP), medio-lateral (ML), and superior-inferior (SI) axes and capture the biomechanical characteristics of the elderly during walking [35]. The derived variables of gait parameters extracted in this study are divided into three categories, including time parameters, angular velocity parameters, and acceleration parameters (Table II).

Temporal Parameters: To estimate the temporal parameters (No.1-4), two essential events need to be detected, i.e., the heel contact event (HC) and toe-off event (TO) [35]. The previous report used adaptive algorithms to determine the timestamp of HC and TO events from the gyroscope ML axis signals of each shank [33]. The adaptive algorithm proved to be robust not only to different characteristic subjects and walking speeds but also to noise in angular velocity signals during movement. Because of the superiority of this algorithm, it is used to detect the essential gait events in this study.

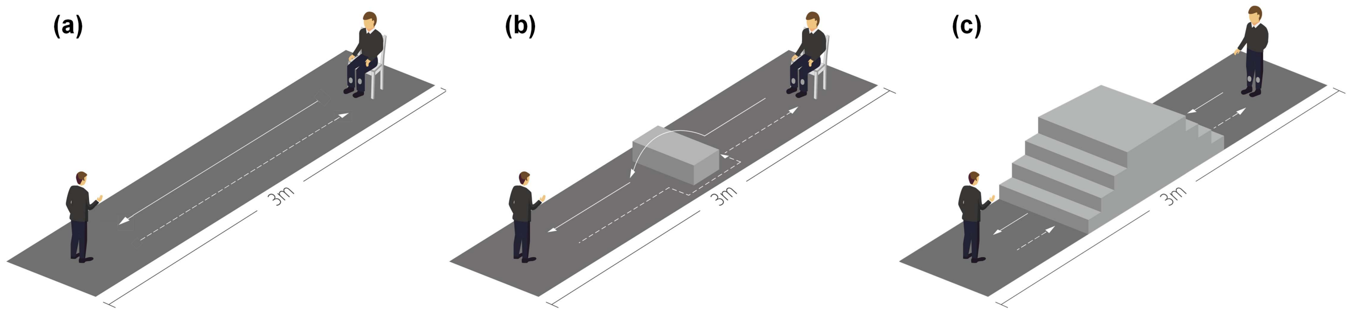

Fig. 2. The environment-adaptive TUG tests. (a) Standard TUG test: Participants stand up from the chair, walk 3 m on a flat ground, then turned back to the chair and sit down. (b) Bypass and Overpass TUG: Participants overpass the obstacle first and bypass the obstacle when returning. (c) Ascent and Descent TUG: Participants stairs ascent first and stairs descent when returning.

TABLE II
SUMMARY OF GAIT PARAMETER CHARACTERISTICS

Feature Number	Feature Name
	Temporal Parameters
1	Stride time (s)
2	Step time (s)
3	Single support (%)
4	Double support (%)
	Angular Velocity Parameters
5	Total walking time (s)
6	Maximum angular velocity (deg/s)
7	Maximum angular velocity radius (deg. m/s)
8	Mean amplitude of mid-swing points (deg/s)
9	Range of mid-swing point amplitude (deg/s)
	Acceleration Parameter
10	Variance (m^2/s^4)
11	Maximum acceleration (m/s^2)
12	Maximum velocity (m/s)
13	Peak power (kg. m/s^2)
14	Maximum forward lean (°)

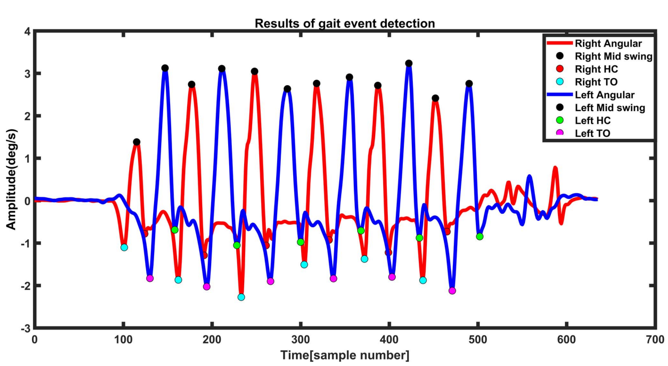

Fig. 3. Mid-swing point derived from ML axis gyroscope signals, and the HC and TO events are marked.

The HC and TO events detected from the gyroscope ML axis signals of each shank are shown in Fig. 3. In addition to the essential gait events, the mid-swing points are marked synchronously. As described in [33], the mid-swing point is easier to detect than HC and TO events, and it corresponds to the maximum point of the angular velocity signal. Therefore, the mid-swing point is generally detected first, then the timestamps of HC and TO events are determined according to the point. The detected HC and TO events are used to calculate the temporal gait parameters listed as follows.

The stride time is the time from the HC point of one foot to the HC point of the same foot. The step time is the time from the HC point of one foot to the HC point of the other foot. The single support is calculated as the time between the TO point and the HC point on the same foot divide by the gait cycle time, which is equal to the swing time of the other foot. The double support is calculated as the time that both feet contact the ground divide by the gait cycle time. As an example, the estimation of right shank stride time and step time are described in Eq. (1) and (2), respectively. In this study, all gait parameters of left and right shank sensor data are merged.

$$\text{stride time } (i) = t_{RHC}(i+1) - t_{RHC}(i) \tag{1}$$

$$\text{step time } (i) = t_{RHC}(i+1) - t_{LHC}(i) \tag{2}$$

where RHC means right heel contact, and LHC means Left heel contact.

Angular Velocity Parameters: Several parameters (No.5-9) related to fall risk can be directly derived from the three axes gyroscope data to analyze the gait characteristics of participants in the EATUG test [10]. These parameters are described as follows.

The total walking time is calculated as the time between the first mid-swing point to the last mid-swing point (Eq. 3). The maximum angular velocity is expressed as the maximum value of the sum of the amplitudes of three axes, which can reflect the swing characteristics of each participant during the test. The maximum angular velocity radius is calculated as the maximum angular velocity times the height of each participant, which can reflect the linear velocity of the shank (the linear velocity is equal to the radius times the angular velocity, and the radius is proportional to the height) (Eq. 4). The mean amplitude of the mid-swing point refers to the average value of all mid-points detected of the ML axis angular velocity signal. The range of the mid-swing point is calculated as the absolute difference between the maximum and minimum of the mid-swing point, which can reflect the range of movement

TABLE III
THE MEAN AND STANDARD DEVIATION OF THE ABSOLUTE AND RELATIVE ERRORS OF THE TEMPORAL PARAMETERS

Temporal Parameters	Absolute error		Relative error	
	Mean	SD	Mean	SD
Stride time (s)	0.0217	0.0081	-0.0087	0.0350
Step time (s)	0.0148	0.0107	-0.0053	0.0123
Single support (%)	1.1100	0.4795	-0.0225	0.0210
Double support (%)	1.4100	0.4228	-0.0338	0.0770

of the shank.

$$\text{total time} = t(Final\ mid - swing) - t(First\ mins - wing) \quad (3)$$

$$\text{Max angular radius} = max\ angular(\text{ML+AP+SI}) * \frac{hight}{100} \quad (4)$$

Acceleration Parameter: Parameters (No.10-14) derived from acceleration signals (e.g., variance [21], peak power [34], etc.) are used to distinguish the risk of falls. To make an effective discriminant analysis of the fall risk under the adaptive TUG tests, the following three axes acceleration signal parameters are extracted.

The variance is calculated as the sum of the dispersion of the acceleration signals for each axis, which represents the vitality measure of the participants. The maximum acceleration refers to the maximum value of the acceleration signal amplitude (ASM) (Eq. 5). The maximum velocity is calculated as the numerical integration of the ASM, while the peak power is the maximum velocity multiplied by the mass of the participant. The Maximum forward lean is expressed as Eq. (6).

$$\text{ASM} = \sqrt{(AP)^2 + (SI)^2 + (ML)^2} \quad (5)$$

$$\theta = \arctan \frac{\sqrt{(AP)^2 + (ML)^2}}{SI} \cdot \frac{180^o}{\pi} \quad (6)$$

C. Validation of Temporal Parameters Using Xsens

Before the EATUG test, a pre-experiment was conducted to verify the reliability of the proposed fall risk system. A total of 10 participants were asked to wear Xsens (https://www.xsens.com/products/xsens-mvn-analyze) and wearable inertial sensors to perform the standard TUG test, then the adaptive algorithms were used to estimate the temporal parameters, i.e., stride time, step time, and support phase [33]. These parameters of the sensor data recorded by Xsens are used as ground truth [36]. The mean and standard deviation of the absolute and relative errors between the inertial sensors and Xsens is shown in Table III.

The results show that the average absolute error of stride time and step time are 21.7 ms and 14.8 ms, respectively. Besides, the average absolute error of the single support phase and the double support phase is not more than 1.5%, indicating the good performance of the inertial sensor and Xsens. The above results prove the high reliability of the proposed system, which has been verified in previous reports [10], [33].

D. Statistical Analysis

In this study, the extracted gait and physiological characteristics are used for statistical analysis. Fisher's exact test is a method suitable for two binary variables, which is used in the gender variable test in Table I. Then, the gait parameters of the elderly in the high-risk and low-risk groups from three TUG tests are compared. The Lillie function in the MATLAB statistical analysis toolbox is used to determine the normal distribution of the 14 variables obtained. For normally distributed variables, the two-sided t-test is used to analyze the significance of the difference between high-risk and low-risk elderly. For non-normally-distributed variables, the Mann-Whitney (†) test is used. P-value less than 0.05 (∗) is considered to be statistically significant. Besides, the influence of different terrain on the gait parameters of the elderly is analyzed, which can reflect the gait adjustment strategies in response to environmental changes. To control multiple comparisons, the Benjamini- Hochberg adjustment is applied to correct the p-value by using the fdr_bh function (the default value of false discovery rate is 0.05) [22].

E. Feature Selection and Classification Model

The gait parameters with significant differences from the three TUG tests are used for feature selection, thereby constructing a support vector machine (SVM) classifier with better prediction performance. In this paper, the LVW (Las Vegas Packaging) method is used for feature selection. Generally, LVW uses a random search strategy to search for feature subsets under the framework of the Las Vegas method. The prediction error of the finally embedded ensemble classifier is used as the evaluation criterion of the selected feature subset. The pseudo-code of the LVW algorithm is shown in Table IV.

The three SVM models are fused into the final prediction model of the EATUG test system by using the voting method. To obtain unbiased classification results, this work uses 5-fold cross-validation to test the performance of the proposed system, which is repeated 10 times. For each verification, 82 subjects are used as training data, and the remaining 21 subjects are used as test data. It also should be noted that the high-risk and low-risk elderly in the training and test data maintain a consistent ratio. The performance of the system is evaluated by the accuracy, sensitivity, and specificity of the prediction results, as shown in Eqs. (7) - (9). The three independent TUG tests and the EATUG test results are described in the ROC curve (Fig. 4).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \quad (7)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (8)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\% \quad (9)$$

where TP represents the number of correct predictions for which the instance is positive; FP represents the number of incorrect predictions that an instance is positive; FN represents the number of false predictions for which the instance is negative; TN represents the number of correct predictions that an instance is negative.

TABLE IV
THE PSEUDO-CODE OF THE LVW ALGORITHM

```
Input Data Set: D;
Feature Set: A;
Learning Algorithm: §;
Stop Condition Control Parameter: T;
Process:
    E =Ğ;
    d = |A|;
    A* = A;
    t = 0;
    while t < T do
        generate feature subsets A';
        d'= |A'|;
        E' = Cross Validation (§('AD));
        if (E' < E) ∨ ((E'=E) ∧ (d' < d)) then
            t = 0;
            E = E';
            d = d';
            A* = A'
        else
            t = t + 1;
        end if
    end while
Output: Feature Subset A*
```

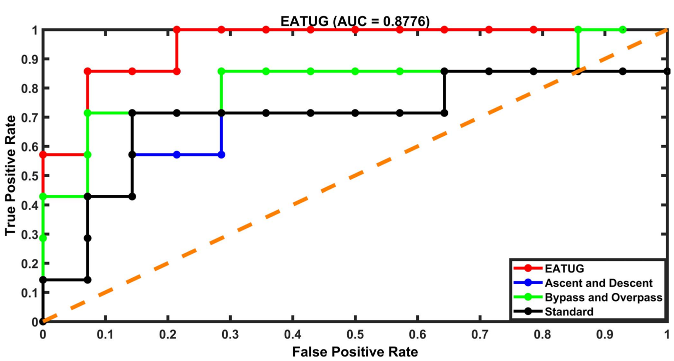

Fig. 4. ROC curves of the output results of three fall prediction tests based on different terrains and the EATUG prediction system.

IV. RESULTS

Table I shows the results of the significance analysis between the cohort characteristics of the high-risk and low-risk groups. There are no significant differences in the cohort characteristics of the height, weight, and gender between the high-risk group and the low-risk group, indicating the risk of falling is not related to these physiological factors. However, there are significant differences in the age of the elderly with different risks of falling. It demonstrates the view that gait variability will increases with age, leading to a higher risk of falling [37]. The statistical analysis results of the remaining various gait characteristics and terrain tests are described as follows.

A. Results of the Significance Analysis Based on Different Fall Risks

Standard TUG Test: The significance analysis results of all parameter variables obtained by the standard TUG test in

TABLE V
SIGNIFICANT ANALYSIS OF PARAMETER DIFFERENCES BETWEEN THE TWO GROUPS OF THE ELDERLY

Feature Number	Mean ± Standard Deviation		
	High-risk	Low-risk	p-value
1	**1.41 ± 0.23**	**1.22 ± 0.18**	**p < 0.001 *** †**
2	**0.70 ± 0.12**	**0.63 ± 0.10**	**p < 0.001 *** †**
3	**39.5 ± 6.98**	**41.3 ± 4.46**	**p < 0.05 *†**
4	**21.9 ± 9.32**	**16.9 ± 4.63**	**0.004 **†**
5	**17.5 ± 5.38**	**12.5 ± 3.22**	**p < 0.001 *** †**
6	**7.45 ± 1.42**	**9.15 ± 1.40**	**p < 0.001 *****
7	**11.5 ± 2.25**	**14.1 ± 2.20**	**p < 0.001 *****
8	**2.18 ± 0.55**	**2.95 ± 0.55**	**p < 0.001*****
9	**2.75 ± 0.88**	**3.30 ± 0.96**	**0.008****
10	**20.8 ± 12.0**	**32.5 ± 18.4**	**p < 0.001 ***†**
11	28.2 ± 10.6	30.1 ± 9.21	0.534 †
12	**1.43 ± 0.23**	**1.80 ± 0.27**	**p < 0.001*****
13	**81.5 ± 22.5**	**105.2 ± 25.8**	**p < 0.001*****
14	38.8 ± 9.22	36.9 ± 10.4	0.292

†: Mann-Whitney U test; Key: ∗p<0.05; ∗∗p<0.01; ∗∗∗p<0.001. Results in bold represent significant discrimination between the two groups.

the high-risk and low-risk groups are shown in Table V. The Mann-Whitney U test is marked with †, while the p-values without †remark refer to the two-sided t-test. The p-value of the test less than 0.05 indicates a significant difference, and the result will be bolded. The result shows significant differences in all parameters except for the maximum acceleration and forwards lean, indicating a good distinction between high-risk and low-risk groups. The gait adjustment of the high-risk elderly will be significantly slower than that of the low-risk group because the high-risk group is accompanied by larger stride time, step time, and double support phases. For the angular velocity and acceleration parameters, the maximum peak power and angular velocity radius of the low-risk group are larger, with an average of 107.6 (kg. m/s^2) and 14.3 (rad. m/s), respectively. In summary, the high-risk elderly is accompanied by a slower gait adjustment and greater double support phases, which reflects the close correlation between the risk of falling and gait control.

Bypass and Overpass TUG Test: Table VI shows the significance analysis results of all the parameter variables obtained through the bypass and overpass TUG test. Except for the maximum acceleration and the range of mid-swing point, the remaining 12 characteristics have significant differences, which are similar to the standard TUG test. For the derivative parameter of the acceleration signal, the variances of the elderly in the high-risk and low-risk groups are 23.1 and 34.3 m^2/s^4, respectively. The variance is expressed as the sum of the fluctuations of the three-axis acceleration signals, reflecting the higher gait dispersion of the low-risk group. Besides, although the Mann-Whitney U test result of the maximum forward lean is less than 0.05 (0.047), the parameter is not suitable as an effective feature to distinguish fall risks.

Ascent and Descent TUG Test: The results of the significance analysis of all the parameter variables obtained through

TABLE VI
SIGNIFICANT ANALYSIS OF PARAMETER DIFFERENCES BETWEEN THE TWO GROUPS OF THE ELDERLY

Feature Number	Mean ± Standard Deviation		
	High-risk	Low-risk	p-value
1	**1.40 ± 0.20**	**1.24 ± 0.18**	**p < 0.001 ***†**
2	**0.71 ± 0.12**	**0.64 ± 0.09**	**p < 0.001*****
3	**39.2 ± 5.57**	**42.5 ± 4.22**	**0.008 **†**
4	**22.5 ± 9.03**	**18.6 ± 5.75**	**0.003****
5	**18.8 ± 4.85**	**14.1 ± 3.66**	**p < 0.001*****
6	**7.58 ± 1.26**	**9.57 ± 1.16**	**p < 0.001*****
7	**12.1 ± 2.11**	**15.2 ± 2.05**	**p < 0.001*****
8	**2.23 ± 0.44**	**2.89 ± 0.49**	**p < 0.001*****
9	3.31 ± 0.58	3.57 ± 0.88	0.135
10	**22.8 ± 14.5**	**33.3 ± 16.1**	**p < 0.001 ***†**
11	35.8 ± 14.8	33.5 ± 10.3	0.693 †
12	**1.55 ± 0.31**	**2.17 ± 0.29**	**p < 0.001*****
13	**92.1 ± 26.2**	**120.4 ± 25.8**	**p < 0.001 ***†**
14	**40.3 ± 9.88**	**35.1 ± 11.5**	**0.047 *†**

†: Mann-Whitney U test; Key: ∗p<0.05; ∗∗p<0.01; ∗∗∗p<0.001. Results in bold represent significant discrimination between the two groups.

TABLE VII
SIGNIFICANT ANALYSIS OF PARAMETER DIFFERENCES BETWEEN THE TWO GROUPS OF THE ELDERLY

Feature Number	Mean ± Standard Deviation		
	High-risk	Low-risk	p-value
1	**1.55 ± 0.44**	**1.28 ± 0.18**	**0.003 **†**
2	**0.76 ± 0.21**	**0.65 ± 0.12**	**0.002 **†**
3	**36.8 ± 8.03**	**42.7 ± 4.26**	**0.002 **†**
4	**32.0 ± 10.1**	**22.8 ± 4.26**	**p < 0.001*****
5	**18.6 ± 4.58**	**14.2 ± 4.15**	**p < 0.001 ***†**
6	**8.11 ± 1.32**	**9.11 ± 1.28**	**p < 0.001*****
7	**12.3 ± 2.02**	**15.3 ± 2.26**	**p < 0.001*****
8	**2.16 ± 0.43**	**3.17 ± 0.72**	**p < 0.001*****
9	3.41 ± 1.21	3.83 ± 0.56	0.312 †
10	**49.1 ± 40.8**	**61.8 ± 32.2**	**0.025 *†**
11	58.1 ± 24.9	51.6 ± 15.2	0.353
12	**1.78 ± 0.36**	**2.02 ± 0.22**	**p < 0.001*****
13	**102.2 ± 29.5**	**122.5 ± 25.6**	**0.005****
14	30.3 ± 9.78	27.8 ± 8.41	0.149

†: Mann-Whitney U test; Key: ∗p<0.05; ∗∗p<0.01; ∗∗∗p<0.001. Results in bold represent significant discrimination between the two groups.

the ascent and descent TUG test are shown in Table VII. There are three characteristics in the acceleration parameter and the angular velocity parameter that have no significant difference, including the range of mid-swing point, the maximum acceleration, and the maximum forward lean. Based on Table V-VII, the remaining 11 parameters have significant differences in all three TUG tests. Because the left and right feet need to contact the surface at the same time during ascending and descending the stairs, the double support phase of the high-risk group in this test is the highest, reaching 31.1 ± 11.1%. In summary, the significance analysis results of the test show that most of the parameters obtained in this experiment have the function of distinguishing the risk of falling.

B. Results of the Significance Analysis Based on Terrain Variability

The significance analysis results of gait parameters based on different terrains are shown in Table VIII. To estimate the gait adjustments of elderly with different fall risks in response to changes in terrain, the high-risk and low-risk groups are listed separately. For the high-risk group, eight variables have significant differences between the standard TUG test and the ascent and descent TUG test, while only three in the standard TUG test and the bypass and overpass TUG test. The results can be explained as the ascending and descending terrain is more complicated. On the other hand, the change in terrain seems to have an insufficient impact on the low-risk group, because the number of parameters with significant differences in all three TUG tests is very close. In other words, the low-risk elderly has stable control to adjust their gait according to the environment.

Table VIII also reflects the sensitivity of different parameter characteristics to the environment. Some parameter variables (e.g., double support, maximum acceleration, etc.) have significant differences between different terrains. On the contrary, there are several parameters (e.g., range of mid-swing point, etc.) that are not sufficiently sensitive to the ascent/descent TUG test and bypass /overpass TUG test, but have significant differences between the other two terrains. Besides, the variability of acceleration parameters is more related to the change of environment, because most acceleration parameters between different terrains have significant differences, while angular velocity and temporal parameters are not. For example, in terms of temporal parameters, except for the double support, the stride time, step time, and single support do not change significantly.

C. Results of the Fall Risk Assessment

The ROC curves of the predicted results of the three independent TUG test and the fused EATUG test system is shown in Fig. 4. The prediction result of the EATUG test system is the best, and the performance of the three independent TUG tests is equivalent. The average accuracy of the standard TUG and EATUG tests for predicting the risk of falling for the elderly is 80.9% and 90.5%, respectively. The accuracy of the EATUG system has increased by 9.52%. Besides, the sensitivity and specificity of the standard TUG and EATUG test results are also estimated. Specifically, the sensitivity based on the standard TUG test is 71.4% and the specificity is 85.7%, while the sensitivity based on the EATUG test is 85.7% and the specificity is 92.9%. Furthermore, the average ROC curve area of the EATUG system is 0.88. In summary, the EATUG system has superior predictive performance, which is a significant improvement on the standard TUG test.

V. DISCUSSION

Because of the drawbacks of the standard TUG test, we constructed an environment-adaptive fall risk assessment system for the elderly and extracted 14 gait parameter variables related to falls. Through the verification of 103 elderly living in the community, the advantages of the system are proved. The main contributions of this research include: 1) The proposed system

TABLE VIII
SIGNIFICANT ANALYSIS OF PARAMETER DIFFERENCES BETWEEN THE ELDERLY OF THE THREE TERRAINS

	High-risk			Low-risk		
Feature Number	Standard Bypass/Overpass	Standard Ascent/Descent	Ascent/Descent Bypass/Overpass	Standard Bypass/Overpass	Standard Ascent/Descent	Ascent/Descent Bypass/Overpass
1	0.651 †	0.078 †	0.203 †	0.441	0.079 †	0.254 †
2	0.587 †	**0.023**	0.170 †	0.327 †	0.081 †	0.313 †
3	0.896 †	0.161 †	0.253 †	0.733 †	0.943 †	0.658
4	0.631 †	**0.002** †**	**0.002**†**	**0.020** †*	**P<0.001**†***	**P<0.001**†***
5	0.273 †	0.569 †	0.549 †	0.086 †	0.109 †	0.948 †
6	0.347 †	0.143 †	0.461 †	**P<0.001** † ***	0.738 †	**0.016** † *
7	0.253 †	0.188 †	0.398 †	**P<0.001** † ***	0.763 †	**0.020** † *
8	0.848 †	1.000 †	0.930 †	0.411 †	0.336 †	0.770 †
9	**0.003** † *	**P<0.001** † ***	0.866 †	**0.001** † **	**0.004** † **	0.284 †
10	0.614	**P<0.001*****	**P<0.001*****	0.930	**P<0.001*****	**P<0.001*****
11	**0.031** †	**P<0.001** † ***	**P<0.001** † ***	**0.011** *	**P<0.001** ***	**P<0.001** ***
12	**0.026** †	**P<0.001**†***	**0.029** †	**P<0.001**†***	**P<0.001**†***	0.168 †
13	0.072 †	**0.006**†*	0.162 †	**0.002**†**	**P<0.001**†***	0.314 †
14	0.485 †	**0.008** †*	**0.003** †*	0.722 †	**P<0.001**†***	**P<0.001**†***

†: Mann-Whitney U test; Result in bold are found to provide significant discrimination between two groups. Key: Adjusted p-values $*p<0.05$; $**p<0.01$; $***p<0.001$ after Benjamini-Hochberg corrections. Original p-values are shown in the table.

can provide richer gait features related to falls and has superior predictive performance; 2) The proposed system can compare the significant differences in gait parameters of elderly with different fall risks under different TUG tests; 3) The proposed system can estimate the influence of changing terrain on gait parameters. The specific contributions of this paper will be discussed in detail as follows.

To simulate the community environment, the EATUG test based on three terrains (levels/obstacles/stairs) is developed, and the significant differences in gait parameters of the elderly with different risks are compared (Table V-VII). The results show that among the 14 reported gait parameters, 11 parameters have significant differences in all three TUG tests, which is consistent with previous studies [10] [34]. Generally, the elderly in the high-risk group has slow walking velocity and a small range of motion, which can be reflected by larger temporal parameters and smaller acceleration and angular velocity parameters. Compared with the standard TUG test that only focuses on the total walking time, the EATUG test system reveals richer gait parameters related to falls, thus providing a more comprehensive evaluation standard for the balance ability of the elderly in the community.

Previous studies have shown that the standard TUG test cannot assess the gait adaptability of the elderly to the environment [38]. In Table VIII, there are eight significantly different variables between the standard TUG test and the ascent and descent TUG test for the elderly in the high-risk group, while only three variables have significant differences in the standard TUG test and the bypass and overpass TUG test. The above results show that the higher the complexity of the environment, the more obvious the change of gait parameters, which has been confirmed in [39], [40]. For the elderly in the low-risk group, the changes in terrain seem to have little effect on their gait parameters, which can be observed by the results of the three TUG tests. In a summary, the high-risk subjects tend to adopt a more rigid stepping strategy in a complex environment, while elderly with low fall risk have stronger gait adaptability to environmental changes [17], [41]. Besides, Table VIII also shows that gait parameters are differently affected by the environment, which will provide substantial guidance for targeted interventions for high-risk elderly encountering environmental changes.

The fall risk assessment system proposed in this paper has been verified on the elderly. The results in Fig. 4 show that the fused EATUG system has the best prediction results, while the remaining three TUG tests have comparable performance. The accuracy of the standard TUG test prediction is 80.9%, which is similar to previous research [42]. However, the specificity of the standard TUG test is significantly higher than the sensitivity, i.e., the recognition rate for low-risk elderly people is higher. In contrast, the EATUG has better sensitivity, which has improved the accuracy of screening for high-risk elderly. Furthermore, the accuracy of the EATUG test is 9.52% higher than that of the standard TUG test, indicating the potential of the system for long-term monitoring of the risk of falling for the elderly.

Wang *et al.* find that multiple falls within a year are more likely to indicate chronic disease and physical impairments, while a single fall may be an accident [22]. Therefore, this study carried out a strict classification procedure in the fall risk assessment, i.e., the combination of fall history and BBS balance test. To some extent, the scale method divides the elderly into high-risk and low-risk groups, rather than falling and non-falling groups, which tends to have better prediction results [43]. Smith *et al.* study the relationship between fall history and the TUG test, and the results show that multiple environmental tests can provide added value for fall assessment [44], [45]. In summary, the evaluation system constructed in this study can provide a more comprehensive prediction of the risk of falls, thereby reducing the misjudgment of falls caused by accidental factors and improving the reliability of the results.

The experimental results show that it is feasible to use the evaluation system constructed in this paper to distinguish the risk of falls in the elderly. It can provide rich fall-related characteristics and show the gait adaptability of different environments. Compared with the standard TUG test, the EATUG system is proven to have more advantages and retains the characteristics of simple tests and high operability. Although Yang *et al.* also established a fall assessment system adapted to the environment, it can only be verified in healthy adults [46]. Relatively speaking, our research has more practical significance. The system meets the conditions for use in a community environment and is expected to be used in the early screening of high-risk elderly people in the future, and to provide them with appropriate balance training guidance and intervention methods, and ultimately reduce fall injuries. For example, Pope *et al.* have shown that multi-factorial exercise and dance-based interventions can effectively reduce the risk of falls for community-dwelling older adults [47].

There are some other improved TUG tests, such as dual-task TUG test, cognitive TUG test, and cognitive TUG dual-task test. Péricles A *et al.* suggested calculating the time for participants to perform TUG reading alternate letters (e.g., “ace”) or count backward by threes from any number between 20 and 100 [48]. Charlotte *et al.* proposed the cognitive timed up-and-go dual-task to improve the performance of the standard TUG test to predict falls in the elderly [49]. Compared with the previous improved TUG test, the EATUG test focuses on the change of the TUG test platform to provide more fall-related information. The TUG test that integrates cognition, dual-task, and environmental adaptation will have optimistic significance for improving high-risk screening.

In recent years, wearable inertial sensors for tracking and classification of human activities have been thoroughly researched. Xsens, as a representative, is widely used in hospitals, research institutions, and laboratories. Although Xsens has the advantages of high reliability and accuracy in motion capture, there are also some problems such as high price and complicated operation, which limit its use in community-dwelling environments. The system in our paper consists of two units, each of which weighs only 30g, and is equipped with a software platform that is simple to operate. Besides, the cost of this system is approximately $150. This work has achieved low-cost and simplified screening of high-risk groups through wearable devices developed in our laboratory.

We acknowledge some research limitations. First, the number of the elderly participating in this study is 103, which is relatively small. To further test the performance of the system, more elderly need to be recruited. Besides, the experiment divided participants into high-risk and low-risk, and we hope to assess the risk of falls for the older adults in more detail. Therefore, subjects with a medium risk of falls need to be labeled. Recently, 86 elderly have been recruited from the community. The system will be further verified in the future to evaluate its prediction results for the high-medium-low fall risk groups. We have reason to believe that through further improvements, the fall risk system proposed in this study can be truly used in a community environment.

VI. Conclusion

In this study, the constructed EATUG fall risk assessment system proved to be an improvement of the standard TUG test. The experiments of the elderly in the community show that the system can not only provide significant differences between the high-risk and low-risk groups but also reflect gait adaptability to environmental changes. Compared with the standard TUG test, the EATUG system has higher prediction accuracy and is expected to be used in clinical and community fall risk screening and intervention guidance.

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References

[1] (2020). *United Nations*. [Online]. Available: https://population.un.org/wpp/

[2] (2020). *World Health Organization*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/falls

[3] *Centers for Disease Control and Prevention (CDC)*. [Online]. Available:https://www.cdc.gov/homeandrecreationalsafety/falls/data/fallcost.html

[4] R. Zhao, W. Bu, and X. Chen, “The efficacy and safety of exercise for prevention of fall-related injuries in older people with different health conditions, and differing intervention protocols: A meta-analysis of randomized controlled trials,” *BMC Geriatrics*, vol. 19, no. 1, p. 341, Dec. 2019.

[5] B. Varriano *et al.*, “Vestibular exercises as a fall prevention strategy in patients with cognitive impairment,” *Can. J. Neurol. Sci./J. Canadien des Sci. Neurologiques*, vol. 47, no. 1, pp. 126–130, Jan. 2020.

[6] E. Sebastião, B. M. Sandroff, Y. C. Learmonth, and R. W. Motl, “Validity of the timed up and go test as a measure of functional mobility in persons with multiple sclerosis,” *Arch. Phys. Med. Rehabil.*, vol. 97, no. 7, pp. 1072–1077, Jul. 2016.

[7] F. M. H. Lam, L. R. Liao, T. C. Y. Kwok, and M. Y. C. Pang, “Effects of adding whole-body vibration to routine day activity program on physical functioning in elderly with mild or moderate dementia: A randomized controlled trial,” *Int. J. Geriatric Psychiatry*, vol. 33, no. 1, pp. 21–30, Jan. 2018.

[8] E. Gervasoni, J. Jonsdottir, A. Montesano, and D. Cattaneo, “Minimal clinically important difference of Berg Balance Scale in people with multiple sclerosis,” *Arch. Phys. Med. Rehabil.*, vol. 98, no. 2, pp. 337–340, 2017.

[9] A. G. S. Panel on Prevention of Falls in Older Persons and B. Geriatrics Society, “Summary of the updated American geriatrics Society/British geriatrics society clinical practice guideline for prevention of falls in older persons,” *J. Amer. Geriatrics Soc.*, vol. 59, no. 1, pp. 148–157, Jan. 2011.

[10] B. R. Greene, A. O'Donovan, R. Romero-Ortuno, L. Cogan, C. N. Scanaill, and R. A. Kenny, "Quantitative falls risk assessment using the timed up and go test," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 12, pp. 2918–2926, Dec. 2010.

[11] E. Barry, R. Galvin, C. Keogh, F. Horgan, and T. Fahey, "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," *BMC Geriatrics*, vol. 14, no. 1, p. 14, 2014.

[12] D. Schoene *et al.*, "Discriminative ability and predictive validity of the timed up and go test in identifying older people who fall: Systematic review and meta-analysis," *J. Amer. Geriatrics Soc.*, vol. 61, no. 2, pp. 202–208, 2013.

[13] E. Nordin, N. Lindelöf, E. Rosendahl, J. Jensen, and L. Lundin-olsson, "Prognostic validity of the timed up-and-go test, a modified get-up-and-go test, staff's global judgement and fall history in evaluating fall risk in residential care facilities," *Age Ageing*, vol. 37, no. 4, pp. 442–448, Jul. 2008.

[14] G. Sprint, D. J. Cook, and D. L. Weeks, "Toward automating clinical assessments: A survey of the timed up and go," *IEEE Rev. Biomed. Eng.*, vol. 8, pp. 64–77, 2015.

[15] L. Hak *et al.*, "Stepping strategies for regulating gait adaptability and stability," *J. Biomechanics*, vol. 46, no. 5, pp. 905–911, Mar. 2013.

[16] M. J. D. Caetano, J. C. Menant, D. Schoene, P. H. S. Pelicioni, D. L. Sturnieks, and S. R. Lord, "Sensorimotor and cognitive predictors of impaired gait adaptability in older people," *J. Gerontol. A, Biomed. Sci. Med. Sci.*, vol. 72, no. 9, pp. 1257–1263, 2017.

[17] D. J. Geerse, M. Roerdink, J. Marinus, and J. J. van Hilten, "Walking adaptability for targeted fall-risk assessments," *Gait Posture*, vol. 70, pp. 203–210, May 2019.

[18] V. Weerdesteyn, B. Nienhuis, and J. Duysens, "Advancing age progressively affects obstacle avoidance skills in the elderly," *Hum. Movement Sci.*, vol. 24, nos. 5–6, pp. 865–880, Oct. 2005.

[19] R. A. Ferraro, G. Pinto-Zipp, S. Simpkins, and M. Clark, "Effects of an inclined walking surface and balance abilities on spatiotemporal gait parameters of older adults," *J. Geriatric Phys. Therapy*, vol. 36, no. 1, pp. 31–38, 2013.

[20] M. Oh-Park, C. Wang, and J. Verghese, "Stair negotiation time in community-dwelling older adults: Normative values and association with functional decline," *Arch. Phys. Med. Rehabil.*, vol. 92, no. 12, pp. 2006–2011, Dec. 2011.

[21] K. Wang *et al.*, "Inertial measurements of free-living activities: Assessing mobility to predict falls," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 6892–6895.

[22] K. Wang *et al.*, "Differences between gait on stairs and flat surfaces in relation to fall risk and future falls," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 6, pp. 1479–1486, Nov. 2017.

[23] U. Lindemann, J. Klenk, C. Becker, and R. Moe-Nilssen, "Assessment of adaptive walking performance," *Med. Eng. Phys.*, vol. 35, no. 2, pp. 217–220, Feb. 2013.

[24] W. R. Young and M. A. Hollands, "Evidence for age-related decline in visuomotor function and reactive stepping adjustments," *Gait Posture*, vol. 36, no. 3, pp. 477–481, Jul. 2012.

[25] Z. Yang, C. Song, F. Lin, J. Langan, and W. Xu, "A smart environment-adapting timed-up-and-go system powered by sensor-embedded insoles," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1298–1305, Apr. 2019.

[26] N. Carson, L. Leach, and K. J. Murphy, "A re-examination of Montreal Cognitive Assessment (MoCA) cutoff scores," *Int. J. Geriatric Psychiatry*, vol. 33, no. 2, pp. 379–388, 2018.

[27] A. A. Alghwiri, "Balance and falls," in *Geriatric Physical Therapy*. 2011, p. 331.

[28] S. W. Muir, K. Berg, B. Chesworth, and M. Speechley, "Use of the berg balance scale for predicting multiple falls in community-dwelling elderly people: A prospective study," *Phys. Therapy*, vol. 88, no. 4, pp. 449–459, Apr. 2008.

[29] J. E. Pizzorno and M. T. Murray, *Textbook of Natural Medicine-E-Book*. Amsterdam, The Netherlands: Elsevier, 2020.

[30] L. Z. Rubenstein and K. R. Josephson, "Falls and their prevention in elderly people: What does the evidence show?" *Med. Clinics North Amer.*, vol. 90, no. 5, pp. 807–824, Sep. 2006.

[31] M. J. D. Caetano, S. R. Lord, D. Schoene, P. H. S. Pelicioni, D. L. Sturnieks, and J. C. Menant, "Age-related changes in gait adaptability in response to unpredictable obstacles and stepping targets," *Gait Posture*, vol. 46, pp. 35–41, May 2016.

[32] R. W. Bohannon, "Reference values for the timed up and go test: A descriptive meta-analysis," *J. Geriatric Phys. Therapy*, vol. 29, no. 2, pp. 64–68, Aug. 2006.

[33] B. R. Greene, D. McGrath, R. O'Neill, K. J. O'Donovan, A. Burns, and B. Caulfield, "An adaptive gyroscope-based algorithm for temporal gait analysis," *Med. Biol. Eng. Comput.*, vol. 48, no. 12, pp. 1251–1260, Dec. 2010.

[34] A. Ejupi, M. Brodie, S. R. Lord, J. Annegarn, S. J. Redmond, and K. Delbaere, "Wavelet-based sit-to-stand detection and assessment of fall risk in older people using a wearable pendant device," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 7, pp. 1602–1607, Jul. 2017.

[35] Y. Diao, Y. Ma, D. Xu, W. Chen, and Y. Wang, "A novel gait parameter estimation method for healthy adults and postoperative patients with an ear-worn sensor," *Physiol. Meas.*, vol. 41, no. 5, 2020, Art. no. 05NT01.

[36] Y. Moon, R. W. Motl, and J. J. Sosnoff, "Monitoring gait in multiple sclerosis with novel wearable motion sensors," *Arch. Phys. Med. Rehabil.*, vol. 97, no. 10, pp. e99–e100, Oct. 2016.

[37] F. Pieruccini-Faria, M. Montero-Odasso, and J. M. Hausdorff, "Gait variability and fall risk in older adults: The role of cognitive function," in *Falls and Cognition in Older Persons*. Springer, 2020, pp. 107–138.

[38] A. Salarian, F. B. Horak, C. Zampieri, P. Carlson-Kuhta, J. G. Nutt, and K. Aminian, "ITUG, a sensitive and reliable measure of mobility," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 3, pp. 303–310, Jun. 2010.

[39] M. F. Vieira *et al.*, "Gait stability, variability and complexity on inclined surfaces," *J. Biomechanics*, vol. 54, pp. 73–79, Mar. 2017.

[40] G. Y. Park *et al.*, "Changes in gait parameters and gait variability in young adults during a cognitive task while slope and flat walking," *Healthcare*, vol. 8, no. 1, p. 30, Feb. 2020.

[41] M. J. D. Caetano *et al.*, "Executive functioning, concern about falling and quadriceps strength mediate the relationship between impaired gait adaptability and fall risk in older people," *Gait Posture*, vol. 59, pp. 188–192, Jan. 2018.

[42] B. R. Greene, E. P. Doheny, C. Walsh, C. Cunningham, L. Crosby, and R. A. Kenny, "Evaluation of falls risk in community-dwelling older adults using body-worn sensors," *Gerontology*, vol. 58, no. 5, pp. 472–480, 2012.

[43] A. Weiss, T. Herman, M. Plotnik, M. Brozgol, N. Giladi, and J. Hausdorff, "An instrumented timed up and go: The added value of an accelerometer for identifying fall risk in idiopathic fallers," *Physiol. Meas.*, vol. 32, no. 12, p. 2003, 2011.

[44] T. Asai, K. Oshima, Y. Fukumoto, Y. Yonezawa, A. Matsuo, and S. Misu, "Association of fall history with the timed up and go test score and the dual task cost: A cross-sectional study among independent community-dwelling older adults," *Geriatrics Gerontol. Int.*, vol. 18, no. 8, pp. 1189–1193, 2018.

[45] E. Smith, L. Walsh, J. Doyle, B. Greene, and C. Blake, "Effect of a dual task on quantitative timed up and go performance in community-dwelling older adults: A preliminary study," *Geriatrics Gerontol. Int.*, vol. 17, no. 8, pp. 1176–1182, 2017.

[46] Z. Yang, C. Song, F. Lin, J. Langan, and W. Xu, "Empowering a gait feature-rich timed-up-and-go system for complex ecological environments," in *Proc. IEEE/ACM Int. Conf. Connected Health: Appl., Syst. Eng. Technol. (CHASE)*, Jul. 2017, pp. 340–347.

[47] J. Pope *et al.*, "Multifactorial exercise and dance-based interventions are effective in reducing falls risk in community-dwelling older adults: A comparison study," *Gait Posture*, vol. 70, pp. 370–375, May 2019.

[48] P. A. Maranhão-Filho, E. T. Maranhão, M. A. Lima, and M. M. D. Silva, "Rethinking the neurological examination II: Dynamic balance assessment," *Arquivos de Neuro-Psiquiatria*, vol. 69, no. 6, pp. 959–963, Dec. 2011.

[49] C. Cardon-Verbecq *et al.*, "Predicting falls with the cognitive timed up-and-go dual task in frail older patients," *Ann. Phys. Rehabil. Med.*, vol. 60, no. 2, pp. 83–86, Apr. 2017.

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