# A multifactorial fall risk assessment system for older people utilizing a low-cost, markerless Microsoft Kinect

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**Research Article**

**Keywords:** Aging, Fall Risk, Multifactorial Assessment, Classification Model, Kinect Sensor, Machine Learning

**Posted Date:** April 14th, 2022

**DOI:** https://doi.org/10.21203/rs.3.rs-1540383/v1

# Abstract

**Background:** Falls among older people are a major public health concern due to their high prevalence and serious consequences. Accurate, convenient, and cost-effective assessment of fall risk is an essential first step for effective fall intervention and prevention. This study aims to develop a multifactorial fall risk assessment system for older people using a low-cost, markerless Microsoft Kinect.

**Methods:** A Kinect-based test battery was designed and implemented in Unity3D to comprehensively assess major fall risk factors on physiological, psychological, and integrated functions. A follow-up experiment was conducted with 102 community-dwelling Korean older women to assess their fall risks and to investigate their prospective falls during a 6-month follow-up period. The participants were divided into a high fall risk group (N=22) and a low fall risk group (N=80) based on prospective falls. Based on 11 variables with significant differences between the two groups, random forest-based machine learning classification models were further constructed to classify the fall risk.

**Results:** Experimental results showed that the high fall risk group performed significantly worse on the Kinect-based test battery, especially in Sit to Stand 5 times (STS5), Choice Stepping Reaction Test (CSRT), and Fall Efficacy Scale (FES). The random forest classification model achieved average classification accuracy of 84.7% with 83.3% sensitivity and 86.1% specificity. In addition, the individual's performance was computed as the percentile value of a normative database so that deficiencies can be clearly visualized and targeted for intervention.

**Conclusion:** These findings indicate that the developed low-cost, markerless Kinect-based multifactorial fall risk assessment system can not only accurately screen out ‘at risk’ older individuals, but also identify potential fall risk factors. The developed system has good potential for effective fall intervention and prevention.


# 1. Background

Fall is a common health concern for older people. Around one-third of older people aged 65 or over experience falls annually, and 35% of them fall recurrently [1]. Fall is a leading cause of fatal injuries and emergency visits, and annual direct medical costs from fall-related injuries are more than $30 billion [2]. Due to the serious adverse consequences of falls, it is critical to assess the fall risks and provide appropriate fall interventions for the older individuals at risk of falling [3].

Various fall risk assessment tools have been developed in the past to evaluate fall risks and screen out ‘at risk’ individuals [4, 5]. Fall risk assessment tools based on self-reported questionnaires and simple performance tests, including Activities-specific Balance Confidence (ABC) Scale, Short Geriatric Depression Scale (SGDS), Berg Balance Scale (BBS) and Tinetti Performance Oriented Mobility Assessment (POMA), are widely used in the clinical field because they are simple and easy to use. However, most of them are subjective or oversimplified to assess fall risks in older people [3, 6]. In addition, many of these tools suffer from the ceiling or flooring effects in fall risk assessment [4]. On the other hand, sophisticated equipment such as Neurocom Balance Master, Biodex Balance System can provide objective, quantitative, and accurate measures for fall risk assessment. Unfortunately, they are expensive, cumbersome and require well-trained staff to operate. With the recent development in sensing technology, the portable sensor based systems for fall risk assessment are gaining popularity due to their advantages over the expensive, cumbersome equipment and subjective questionnaires or oversimplified clinical tests [7]. Inertial sensors, especially accelerometers and gyroscopes, have been widely used for fall risk assessment due to their excellent capabilities to monitor human motions and wearability. Qiu et al. [6] developed a fall risk assessment system for older people using five inertial sensors and an inertial-sensor based test battery. Similä et al. [8] developed models to predict balance deficits and identify fall risk via two accelerometers in balance and walking tests. Even though these studies are valuable and have achieved reasonable fall risk classification accuracies, wearing inertial sensors on the body locations accurately is not an easy task for older

people and it may cause discomfort or inconvenience due to obtrusiveness from the attached sensors[9]. Furthermore, the accuracy of the fall risk assessment system depends on the number of wearable inertial sensors and their attached locations [3], which needs to be further optimized.

Microsoft Kinect holds promise to overcome the limitations of inertial sensors for developing a fall risk assessment system. Kinect v2 is a low-cost ($249 for Kinect v2 released in 2014), markerless sensing device which can real-time track human 3D full-body motions in form of 25 skeletal joints based on a RGB-D sensor (image and depth sensors) and embedded gesture recognition algorithms. Therefore, it is unobtrusive and convenient for older people because they do not need to wear the sensors. In addition, it can enable older users to effectively interact with the developed fall risk assessment system with their natural gestures directly (natural user interface). Thus, a Kinect-based fall risk assessment system can facilitate the healthcare applications (self-assessment, diagnose, and rehabilitation) and maximize older people's adoption due to unobtrusiveness, low-cost, natural user interface, and convenience [10, 11]. The position accuracy of human skeletal joints from Kinect was also confirmed to be acceptable, even if it is not as good as the optical motion capture system [12].

A few studies have attempted to implement fall risk assessment tests using the Kinect for older people and patients of high fall risks [13–17]. Researchers utilized static balance test [13], sit-to-stand test [14], timed up and go test [15, 16], and choice reaching reaction test [17], and they reported that various outcome measures (such as sway range, completion time, step length, number of steps, and reaction time) from those tests showed the statistically significant group differences between the high fall risk group and the low fall risk group. However, outcome measures of statistical significance do not necessarily guarantee sufficient discriminative power and good accuracy for fall risk classification. Two studies further examined the discriminative power of their proposed Kinect-based fall risk assessments. Tripathy et al. [18] classified fallers and non-fallers with 74.5% overall accuracy based on a single-leg standing test, and Kargar et al. [19] discriminated between high and low fall risk groups with 67.4% accuracy based on the timed up and go test. These research studies indicated that it is difficult to accurately screen out people who are at high fall risk with just one or a few simple tests. The test battery should be comprehensive and multifactorial since falls typically happen due to the combination and interaction of different fall risk factors. In addition, all the developed Kinect-based fall risk assessment systems can only assess the overall fall risk but lack the ability to further diagnose potential risk factors that increase one's fall risk, thus, they are of limited clinical value in determining tailored fall intervention programs for effective treatment. In order to overcome existing limitations, this research aims to develop a multifactorial fall risk assessment system with diagnosis ability for older people utilizing a low-cost, markerless Microsoft Kinect v2 and a comprehensive while practical test battery.

## 2. Materials And Methods

# 2.1. Kinect-based system setup and multifactorial test battery for fall risk assessment

Considering the practical tracking range of Kinect (max. range of 4.5 m for Kinect v2) and necessary space for different tests, the Kinect-based system setup (Fig. 1) was first optimized for easy and robust data acquisition through our internal tests. A Kinect v2 device was placed on a table, 3.2 m away from a chair and 0.7 m above the ground. A cone and a balance pad (Airex) were placed in between the Kinect device and the chair for some subtests in the test battery.

A list of representative fall risk factors covering physiological (subsystems for sensory input, central processing, and motor response), psychological (fear of falling, depression etc.), and integrated functions (gait and mobility, postural adjustments etc.) were generated from the literature review of previous studies. A corresponding Kinect-based multifactorial test battery to assess those risk factors was designed afterwards. In order to make this test battery to be

scientific and practical, each subtest under the test battery should be not only valid and reliable for assessing corresponding risk factors, but also simple and quick for older people to undertake. Our developed test battery (Fig. 2) was composed of seven subtests to assess intrinsic fall risk factors for physiological, psychological, and integrated functions [6]: 1) Sensory Organization Test-SOT for sensory inputs and static balance, 2) Limit of Stability-LOS for postural stability, 3) Sit to Stand 5 times-STS5 for postural adjustment and lower-limb strength, 4) Timed Up and Go-TUG for mobility and dynamic balance, 5) Range of Motion test-ROM for joint movement and flexibility, 6) Choice Stepping Reaction Test-CSRT for sensorimotor and cognitive function, and 7) Short Fall Efficacy Scale-FES for psychological risk factor, especially fear of falling. All subtests were developed using Kinect SDK 2.0 (Microsoft Corporation, Redmond, Washington, United States) and Unity3D (Unity Technologies, San Francisco, California, United States), and they were adopted from previous research with modifications if necessary.

The walking distance of standard TUG was modified from 3 m to 2 m due to the limited tracking range of Kinect. The maximum tracking range of Kinect is about 0.8–4 m and the actual range of stable full-body tracking is even smaller. We followed the earlier studies and chose 2 m walking distance for Kinect-based TUG [16, 20]. CSRT has two versions: CSRT-M using a rubber pad and CSRT-E using an electronic pad [21]. Ejupi et al. [17] developed Kinect-based CSRT with two stepping panels on the left and right, however, the present study implemented Kinect-based CSRT with four stepping panels (left, front-left, right, and front-right) to keep the same design as the original CSRT. Each stepping panel was randomly illuminated in one trial for a total of five times, so the total trials for four panels were 20. Five-second break was given in between trials. Figure 2 shows the implemented subtests to assess fall risk, and Table 1 describes the detailed protocol of each subtest and its representative outcome measures.

Table 1
A Kinect-based multifactorial test battery to assess fall risk: subtests and representative outcome measures

| Subtest name | Subtest protocol | Representative outcome measures |
|---|---|---|
| Sensory Organization Test (SOT) | Stand under the different conditions (C1–C4) while maintaining balance for 20 seconds<br><br>C1: Eyes open on firm surface/ground<br><br>C2: Eyes closed on firm surface/ground<br><br>C3: Eyes open on soft surface (balance pad)<br><br>C4: Eyes closed on soft surface (balance pad)<br><br>*(Each condition was repeated twice)* | Equilibrium Score (ES): The average center of gravity (COG) sway for each condition in AP/ML directions;<br><br>Composite Equilibrium Score (CES): A weighted average of equilibrium scores under the 4 conditions. It is derived from the individual equilibrium scores;<br><br>Sensory analysis ratios: Ratios of the average ESs of C2 (somatosensory), C3 (visual), and C4 (vestibular) to ES of C1 (baseline);<br><br>Sway area: Sway area of COG under each of the condition;<br><br>Sway area ratios: Ratios of sway areas of C2, C3, C4 to sway area of C1 |
| Limit of Stability (LOS) | Shift the body weight and reach the arm as far as possible to different directions while maintaining balance<br><br>C1: Reach forward<br><br>C2: Reach leftward<br><br>C3: Reach rightward<br><br>*(Each condition was repeated twice)* | Actual reach distance: The average distance of an outstretched arm in a maximal reach from the beginning;<br><br>Normalized reach distance: Actual reach distance normalized by the stature;<br><br>COG reach distance: The average length of COG position in a maximal reach from the beginning;<br><br>Lateral imbalance: Ratio between lateral reach distances (The larger reach distance is always a numerator) |
| Sit to Stand 5 times (STS5) | Stand and sit on a chair 5 times as fast as possible<br><br>*(The test was repeated twice)* | Total completion time: The average elapsed time from the beginning to last standing up;<br><br>Average time of sit-stand (stand-sit): The average elapsed time from sitting to standing or standing to sitting;<br><br>COG moving distances: The average COG moving distance in AP and ML directions while sit-stand and stand-sit |

C1–C4: condition 1–condition 4, AP: anterior-posterior, ML: medio-lateral, COG: center of gravity

| Subtest name | Subtest protocol | Representative outcome measures |
|---|---|---|
| Timed Up and Go (TUG) | Stand from a chair, walk 2 m, turn, come back, and sit on the chair with normal walking speed<br><br>*(The test was repeated twice)* | Total completion time: The average elapsed time to complete the TUG test;<br><br>Elapsed time of each phase: The average elapsed times for sit-to-stand, walking, turning, and stand-to-sit phases;<br><br>Duration of each phase (%): The percentage of the elapsed time of each phase to the total completion time;<br><br>Step width: The average step width in the walking phase;<br><br>Step duration: The average duration of each step in walking phase;<br><br>Number of steps: The total number of steps in walking phase |
| Range of Motion test (ROM) | Sit on the chair, fully extend a knee and hold for 2 sec, then bend the knee and hold for 2 sec<br><br>*(Repeat 3 times for each knee)* | Knee flexion angle: The average of minimal knee angles while bending the knee;<br><br>Knee extension angle: The average of maximal knee angles while extending the knee;<br><br>Knee range of motion: The average of difference between knee extension and flexion angles |
| Choice Stepping Reaction Test (CSRT) | Step on an illuminated panel as fast as possible *(four random panels: left, left-front, right and right-front; each panel was illuminated five times)* | Total completion time: The total elapsed time to complete 20 trials of the test;<br><br>Reaction time: The average time between when a panel is illuminated and a foot starts to move;<br><br>Movement time: The average time between when a foot starts to move and when the illuminated panel is stepped |
| Short Fall Efficacy Scale (FES) | Choose the right level of concern about falling during seven daily activities | FES score: The total score of seven evaluation questions (Range: 7–28) |
| C1–C4: condition 1–condition 4, AP: anterior-posterior, ML: medio-lateral, COG: center of gravity | | |

## 2.2 Experimental Participants

All participants were community-dwelling volunteers from three cities (Cheongju, Sejong, and Incheon) in South Korea. The eligibility criteria were as follows: age ≥ 65 years, female, and able to walk independently without the use of assistive devices. This study focused on older women because they were reported to have higher fall risks than older men [22, 23]. In total, 106 community-dwelling older Korean women participated in this study. This sample was based on convenience sampling instead of random sampling due to challenges from COVID-19 pandemic. Each participant gave the written informed consent prior to participation. All participants performed the seven subtests sequentially (in the order of SOT, LOS, STS5, TUG, ROM, CSRT, and FES) and completed the test battery within 25-min. Their self-reported

history of falls in the past 1-year was also collected. The study was ethically approved by KAIST Institutional Review Board (IRB No: KH2020-015).

## 2.3 Investigation of prospective falls

The events of prospective falls were investigated over six months after the fall risk assessment [24]. The investigation was conducted biweekly by text message or by telephone if there was no text reply. Four participants lost fall monitoring as three failed to follow up and one decided to withdraw from the study. Therefore, a total of 102 (106-4) participants remained in this study and their data were further analyzed.

Participants who experienced prospective falls during the 6-month follow-up period were classified as 'high fall risk group'; otherwise, they were classified as 'low fall risk group'. According to the above criteria, 22 (21.6%) older participants belonged to the high fall risk group and the rest of 80 (78.4%) participants belonged to the low fall risk group. Table 2 shows the sample characteristics of the high and low fall risk groups. Compared with the low fall risk group, the high fall risk group was significantly older ($p = 0.048$) and experienced more falls in the past 1-year ($p = 0.046$), but there were no significant differences in height, weight and BMI ($p > 0.05$).

Table 2
Sample characteristics of high fall risk group and low fall risk group

| Characteristics | High fall risk group ($N_1 = 22$) | Low fall risk group ($N_2 = 80$) | #Two-sample comparison, p-value |
|---|---|---|---|
| Age (years) | 76.6 ± 5.0 | 74.2 ± 5.1 | 0.048 |
| Height (cm) | 155.1 ± 4.1 | 154.8 ± 4.6 | 0.790 |
| Weight (kg) | 58.3 ± 6.8 | 57.2 ± 6.7 | 0.523 |
| BMI (kg/m$^2$) | 24.0 ± 3.1 | 23.9 ± 2.8 | 0.883 |
| Fall history in the past 1-year | | | 0.046 |
| Yes | 11 (33.3%) | 22 (66.7%) | |
| No (reference) | 11 (15.9%) | 58 (84.1%) | |

#Continuous variables were analyzed with two-sample t-tests and categorical variables were analyzed with chi-squared test.

## 2.4 Kinect data processing and feature extraction

Figure 3 shows 25 skeletal joints tracked by Kinect v2 and their coordinate system. The joint position data collected by Kinect were first filtered by a first-order Butterworth low-pass filter with a cutoff frequency of 10 Hz [25] to remove noise in the time-series data. Then various algorithms were developed for extracting meaningful fall risk measures from the skeletal data. During this process, different skeletal joints were used for different subtests due to their high relevance with the corresponding subtests and the specific movement patterns recorded during each subtest [6]. For example, hand joints were used to compute reach distances in LOS; for ROM, hip, knee, and ankle joints were used; while for TUG, spine base, spine shoulder, elbow, and foot joints were used.

In order to simplify the explanation of algorithm development for extracting important features from the Kinect data to compute outcome measures in subtests, one of the most complicated subtests for feature extraction-TUG was illustrated

as a representative example (Fig. 4). The entire TUG task was divided into four phases: sit-to-stand, walking, turning, and stand-to-sit as Kargar et al. [19]. The turning phase was determined by the absolute difference between x-coordinates of the left and right elbows as shown in Fig. 4B (top, left). When turning, the x-coordinates of left and right elbows will theoretically overlap. Therefore, the position difference between two elbows along the x-axis will first reach to a local minimum and then return to the original difference. This pattern would happen again in the transition between the walking phase and the stand-to-sit phase because the subject should turn around and sit on a chair. The entire TUG phase (from start to end) was extracted by using the z-coordinates of the spine base joint as shown in Fig. 4B (top, right). Since the spine base joint was located close to the center of mass, its position data tracked by Kinect was very stable. The initial moment when the z-coordinate of this joint starts to decrease is the start moment of the test, and the moment when the z-coordinate becomes the smallest is the turning moment. After turning, the z-coordinate will continue to increase until it stabilizes at the initial position at the end of the test. After the starting point, the end of the sit-to-stand phase (i.e. just before the walking phase) and start of the stand-to-sit phase (i.e. right after the walking phase) were determined by comparing the y-coordinate of the spine shoulder joint with its height when full standing, as shown in Fig. 4B (bottom, left). Gait-related outcome measures were derived from two foot joints. As shown in Fig. 4B (bottom, right), the local peaks of the difference between the z-coordinates of the left and right feet were related to the gait cycle and characteristics, and they were used to further calculate the number of steps, step width, and step duration. Due to the validity issue [20, 26], all gait outcome measures were calculated using only data before the turning phase.

## 2.5 Statistical analysis and fall risk modeling

Figure 5 summarizes the whole process of statistical data analysis and fall risk modeling. Two-sample t-tests were conducted first on all outcome measures from seven subtests to identify significant ones between high and low fall risk groups. Then, a Receiver Operating Characteristic (ROC) analysis was performed with each significant outcome measure to examine the discriminative power on classifying the fall risk groups. Fall risk classification models were constructed afterwards by using only significant outcome measures in both t-test and ROC analysis as predictors. The same analysis process was performed for the sample characteristic variables in Table 2, which were collected through surveys and easy to be included in the fall risk classification model. For significance tests of categorical variables, such as the history of falls, Chi-squared test and univariate logistic regression were used (Phase 1). Because the performance of a classification model can be different how to split training and test datasets, three exclusive dataset splits were made to investigate the overall performance of classification models. Phases 2 and 3 in Fig. 5 represent an example to develop a fall risk classification model using a dataset split. Each dataset split consisted of 70% of the training set and 30% of the test set. Due to the concern of potentially biased classification results caused by the high imbalance between high and low fall risk groups (22 vs 80), the Synthetic Minority Over-sampling Technique (SMOTE) was applied for the training set before constructing the classification model, as suggested by previous studies [27] (Phase 2). Afterwards, the classification model was constructed by using the random forest algorithm for the oversampled training set (Phase 3). The hyperparameters of the random forest algorithm were tuned by using the random search method with 3-fold cross-validation, and the final model was evaluated by the test set. The balanced accuracy, sensitivity and specificity were used to evaluate the model classification performance, as the high and low fall risk groups were imbalanced [28].

Statistical analysis of significance tests was conducted using IBM SPSS Statistics 20 (IBM Corporation, New York, United States) with a significance level of 0.05. Kinect data were processed on Visual Studio 2019 (Microsoft Corporation, Redmond, Washington, United States). Data augmentation and classification model construction were performed using the imbalanced-learn and scikit-learn packages in python [29].

# 3. Results

## 3.1. Significant outcome measures and sample characteristics to distinguish high and low fall risk groups

Among all 66 outcome measures from seven subtests of the developed Kinect-based test battery (see details in Appendix Table A.1), 11 outcome measures were significantly different between high and low fall risk groups in terms of two-sample t-tests (Table 3). Among them, 10 outcome measures had significant discriminative power from ROC analysis (Table 3). According to results of the significance tests, the high fall risk group had the following characteristics: larger body sway and lower equilibrium score in SOT, shorter reach distance in LOS, longer time to complete STS5, shorter turning phase during TUG, longer time to complete CSRT, and higher total score in FES. There was no significant outcome measure from ROM.

Table 3
Significant outcome measures of the Kinect-based test battery to distinguish high and low fall risk groups

| Outcome measures | Two-sample t-test | | | ROC analysis | |
|---|---|---|---|---|---|
| | High fall risk group ($N_1$ = 22) | Low fall risk group ($N_2$ = 80) | p-value | AUC (Area under curve) | p-value |
| SOT: ES of C4 (AP)# | 81.6 ± 7.1 | 85.4 ± 5.0 | 0.029* | 0.668 | 0.016* |
| SOT: Composite equilibrium score | 89.7 ± 3.3 | 91.2 ± 1.8 | 0.049* | 0.626 | 0.072 |
| SOT: Vestibular ratio# | 91.4 ± 5.4 | 94.1 ± 3.2 | 0.037* | 0.647 | 0.036* |
| LOS: Actual reach distance (forward)# (cm) | 24.2 ± 5.3 | 27.7 ± 6.9 | 0.032* | 0.664 | 0.019* |
| LOS: Normalized reach distance (forward)# (%) | 18.0 ± 4.0 | 20.6 ± 5.0 | 0.025* | 0.670 | 0.015* |
| STS5: Total completion time# (sec) | 12.0 ± 2.6 | 10.2 ± 2.7 | 0.006* | 0.702 | 0.004* |
| STS5: Mean sit-to-stand time# (sec) | 1.1 ± 0.2 | 0.9 ± 0.2 | 0.003* | 0.703 | 0.004* |
| STS5: Mean COG moving distance in sit-to-stand (AP)# (cm) | 11.1 ± 3.3 | 9.6 ± 3.0 | 0.047* | 0.647 | 0.035* |
| TUG: Proportion of the turning phase# (%) | 17.2 ± 3.9 | 19.8 ± 3.8 | 0.007* | 0.661 | 0.027* |
| CSRT: Total completion time# (sec) | 29.2 ± 9.1 | 24.7 ± 7.2 | 0.021* | 0.695 | 0.008* |
| FES: FES score# | 14.8 ± 5.0 | 11.9 ± 3.9 | 0.005* | 0.676 | 0.012* |
| * Significant difference with $p \leq 0.05$; | | | | | |
| # Significant outcome measures in both two-sample t-test and ROC analysis | | | | | |

As shown in Table 2, age and fall history were significant sample characteristics, and further univariate logistic regression analysis (Table 4) showed that fall history had significant discriminative power between the high and low fall risk groups (odds ratio = 2.636; p = 0.050). However, age didn't show significant discriminative power between the high

and low fall risk groups according to the ROC analysis (AUC = 0.634; p = 0.055). Therefore, only the fall history was further included in fall risk classification models.

Table 4
Significant sample characteristics to distinguish high and low fall risk groups

| Sample characteristics | Chi-squared test | | | Univariate logistic regression | |
|---|---|---|---|---|---|
| | High fall risk group ($N_1$ = 22) | Low fall risk group ($N_2$ = 80) | p-value | Odds ratio | p-value |
| Fall history in the past 1-year | | | 0.046* | 2.636 | 0.050* |
| Yes | 11 (33.3%) | 22 (66.7%) | | | |
| No (reference) | 11 (15.9%) | 58 (84.1%) | | | |
| * Significant difference with $p \leq 0.05$ | | | | | |

# 3.2. Performance of fall risk classification models

Table 5 summarizes the fall risk classification performance of random forest classification models for three different test sets. The classification model achieved an average balanced classification accuracy of 84.7%, sensitivity of 83.3%, and specificity of 86.1%.

Table 5
Classification performance of fall risk classification models for the test set in each dataset split

| Classification outcome | High fall risk group | | Low fall risk group | | Balanced accuracy, % | Sensitivity, % | Specificity, % |
|---|---|---|---|---|---|---|---|
| Test set | ($N_1$ = 6) | | ($N_2$ = 24) | | | | |
| | TP | FN | FP | TN | | | |
| Dataset split 1 | 5 | 1 | 7 | 17 | 77.1 | 83.3 | 70.8 |
| Dataset split 2 | 5 | 1 | 1 | 23 | 89.6 | 83.3 | 95.8 |
| Dataset split 3 | 5 | 1 | 2 | 22 | 87.5 | 83.3 | 91.7 |
| **Average** | **5** | **1** | **3.3** | **20.7** | **84.7** | **83.3** | **86.1** |
| TP: True positive, FN: False negative, FP: False positive, TN: True negative; | | | | | | | |
| Balanced accuracy = (Sensitivity + Specificity) /2 | | | | | | | |

# 3.3. Diagnosis of potential fall risk factors

Inspired by Lord et al.'s physiological profile approach for assessing fall risks [30], our developed fall risk assessment system can further diagnose the potential fall risk factors based on the performance of the subtests. An individual's performance in relation to a normative database of 106 tested older subjects were computed as percentile values so that deficiencies (in red) can be clearly visualized and targeted for intervention (Fig. 6). Figure 6 shows typical examples of diagnostic reports for individuals with low (Fig. 6, left) or high fall risks (Fig. 6, right). It not only provides an overall fall risk score equal to the fall probability estimated by the random forest classification model, but also provides detailed

scores related to six significant fall risk factors that correspond to each subtest result. For example, the older individual at high fall risk in Fig. 6 (right) has a probability of falling at 69%, and potential fall risk factors including deficiencies in cognitive function, postural stability, confidence in daily activities, and lower-limb function.

# 4. Discussion

We developed a Kinect-based multifactorial fall risk assessment system for older people. It is low-cost, markerless, and convenient to use. A comprehensive test battery consisting of seven subtests was designed and implemented using Microsoft Kinect v2 and Unity3D. Among seven subtests, three were designed to assess physiological risk factors: SOT for sensory inputs and static balance, CSRT for sensorimotor and cognitive function, and ROM for lower-limb function. One iconized FES questionnaire was designed to assess psychological risk factor, especially on the fear of falling. The rest three subtests were designed to assess the integrated functions: STS5 and LOS for the postural stability, adjustment and response assessment; and TUG for the gait mobility and dynamic balance assessment. A follow-up experiment with 102 community-dwelling older women and an investigation of their prospective falls showed that our developed system can not only classify the overall fall risks accurately but also identify the potential fall risk factors for effective interventions.

## 4.1. Kinect-based test battery and significant outcome measures to distinguish high and low fall risk groups

Ten outcome measures from the developed Kinect-based test battery and 1-year fall history showed both significant statistical difference and good discriminative power to distinguish high and low fall risk groups (Tables 3 and 4). When compared with the low fall risk group, the high fall risk group had more falls in the past 1-year, larger body sway in SOT, and shorter reach distance in LOS. In addition, the high fall risk group showed higher fear of falling (larger score in FES) and took longer time to complete STS5 and CSRT, while had a shorter turning phase during TUG. These results are largely consistent with previous studies which reported the major risk factors for fallers [4, 6, 31–33]. Importantly, at least one outcome measure from each of seven subtests in the Kinect-based test battery showed significant group difference and good discriminative power, with the exception of ROM, indicating that the proposed subtests were effective to assess fall risk in older people. ROM was the only subtest that did not have any significant outcome measure for classifying fall risk. Even though earlier studies have reported that the range of motion of ankle (e.g., dorsiflexion or plantarflexion) plays an important role in assessing fall risk, strength is more important than range of motion for knee-related measures to assess fall risk [34, 35]. However, due to the poor tracking quality of ankle joints by Kinect, we only measured the range of motion of the knee, not the ankle [36].

ROC analysis showed that some Kinect-based outcome measures were more discriminative for fall risk than others (Table 3). Mean sit-to-stand time and total completion time of STS5 showed the highest discriminative power, followed by total completion time of CSRT and FES score. Overall, this study suggests that STS5, CSRT, and FES are important tests that should be included in the multifactorial fall risk assessment as much as possible.

It should be noted that even though the TUG is a widely used test in the clinical field to assess fall risk in patients at high risk of falling, the total completion time of TUG was not a significant outcome measure for predicting future falls of the community-dwelling older people in this study. Although the association of TUG completion time with future falls is controversial, it is generally agreed that TUG completion time has limited ability to predict future falls, while it is effective to identify the history of falls [37–39]. The potential reason is that a 3m walk can be insufficient to assess fall risk, therefore, a longer walking distance (5 to 6m) is necessary to fully assess mobility and predict falls [37]. In our study, due to the limited trackable range of Kinect, the TUG walking distance was even shorter (2m) than the original 3m TUG, so it would be difficult to expect sufficient predictive power. Whereas regarding the history of falls, since TUG is tested after

participants already experienced falls, their behavior patterns may be different from the moments before falls - more conservative and safer [3]. Interestingly, the high fall risk group had a shorter turning phase during TUG in comparison to the low fall risk group. As shown in Appendix Table A.1, the high fall risk group not only required slightly longer times in sit-to-stand, walking, stand-to-sit phases, but also total completion time, while took a slightly shorter time in the turning phase despite statistical insignificance. It seems that the proportion of the turning phase became significantly different between groups by accumulating these small differences. Furthermore, this may indicate that the high fall risk group takes longer time in risky transitions such as sit-to-stand, stand-to-walk, and walk-to-sit [3, 40].

## 4.2. Accuracy of fall risk classification

Based on the proposed Kinect-based test battery, a follow-up experiment with 102 older subjects showed that our fall risk classification model can achieve an average accuracy of 84.7%, with 83.3% sensitivity, and 86.1% specificity. Several earlier studies attempted to develop wearable inertial sensor-based fall risk assessment systems. Caby et al. [41] tested walking tasks for older people, and classified high and low fall risk groups with 75–100% accuracies. However, the accuracies were based on very limited sample size of 20 and thus it could be difficult to generalize. Liu et al. [42] and Gadelha et al. [43] performed TUG, STS, step or muscle quality tests to evaluate fall risk of 68 and 167 subjects, respectively. However, their reported fall classification accuracies were 71% and 69.5%, which may not be sufficient for practical use. Yamada et al. [44] explored the preliminary validity of using Nintendo Wii game programs to assess fall risk in older people. They tested 45 older women and correctly classified 88.6% of the cases (faller or non-faller) based on the basic step scores from the game program. Unfortunately, even though it was a preliminary study, we did not find follow-up studies to verify the major findings and classification accuracy. Recently, Qiu et al. [6] attached five inertial sensors and performed a multifactorial fall risk assessment test battery on 196 community-dwelling Korean older women. Their fall classification model achieved the overall accuracy of 89.4%, with 92.7% sensitivity and 84.9% specificity. Overall, the accuracy of our Kinect-based fall risk assessment system (84.7%) was comparable to those of previous inertial sensor-based fall risk assessment systems. Additionally, inertial sensors need to be worn accurately by older people and can induce movement interference and discomfort, while Miscrosoft Kinect is a markerless device, which does not require the subject to wear bothersome sensors and can automatically detect major body landmarks during testing. Therefore, the Kinect-based fall risk assessment system should be more convenient and practical for older subjects.

Even though many studies assessed fall risk using Kinect devices, and reported statistically significant measures between low and high fall risk groups [13–17], only three comparable studies [18, 19, 45] further attempted to classify individuals at high or low fall risk using Kinect-based test protocols and their outcome measures (Table 6). Table 6 demonstrated that more comprehensive test protocols tend to produce higher classification accuracy, although it is difficult to directly compare these studies due to different samples, labeling criteria for fall risk group and classification models. Kargar et al. [19] and Tripathy et al. [18] implemented a single test such as TUG and single-leg standing to assess fall risk, and the accuracies were 67.4% and 74.6%, respectively. Whereas, our study and Colagiorgio et al. [45] achieved accuracies of around 85% with comprehensive and multifactorial test protocols. The higher classification accuracy from comprehensive test protocols could be explained by the fact that fall is a complex multifactorial phenomenon [32] and the test protocol should be also multifactorial for more accurate fall risk assessment. We found that Colagiorgio et al. [45] reported slightly higher classification accuracy than ours (85.8% vs. 84.7%), even though our test protocol was more comprehensive. This may be due to their mixed samples of old and young adults and different labelling criteria for the high fall risk group. Note that only our study labeled high and low fall risk groups based on the prospective fall, which is difficult to obtain but should be the most valid criterion for predicting fall risk [46]. It is worth noting that we have carefully designed those seven simple and quick subtests for the Kinect-based test battery, in order to achieve a good balance between the accuracy of fall risk assessment, the efficiency of the test time, and the

convenience of the test subject. All older participants in this study can complete the entire test battery within 25 minutes, further demonstrating the practicality and potential of our newly developed Kinect-based fall risk assessment system.

Table 6
Comparison of Kinect-based fall risk assessment studies and fall risk classification performances

| Study | Sample | Test protocol | Labelling criteria for individuals at high fall risk | Classification models | Model validation | #Balanced accuracy of the best model (%) |
|---|---|---|---|---|---|---|
| Colagiorgio et al. (2014) [45] | 66 older adults (Age: 76 ± 10) 13 young adults (Age: 26 ± 5) | Static balance test (sitting, standing); Dynamic balance test (STS, turn 360°) | Combination of Tinetti, BBS, BESTest < 29 (33) | DT, KNN, MC, NB, SVM | Bootstrap technique | SVM: 85.8 (Sens: 80.2, Spec: 91.3) |
| Kargar et al. (2014) [19] | 12 older adults (Age: 65–90) | TUG | Physician examination | SVM | Leave-one-out cross-validation | SVM: 67.4 (Sens: 67.5, Spec: 67.3) |
| Tripathy et al. (2018) [18] | 224 patients with neuro-physiological disorders (Age: 67.5 ± 14) | Single-leg standing | BBS < 45 (56) | ELM, KNN, RF, SVM | 5-fold cross-validation | RF: 74.6 (Sens: 74.8, Spec: 74.3) |
| Our Study (2022) | 102 community-dwelling older women (Age: 74.7 ± 5.1) | SOT, LOS, STS5, TUG, ROM, CSRT, FES | At least one fall during a 6-month follow-up | RF | 3-fold cross-validation | RF: 84.7 (Sens: 83.3, Spec: 86.1) |

# Balanced accuracy was calculated based on the reported sensitivity and specificity from the earlier studies

BBS: Berg Balance Scale, BESTest: Balance Evaluation System Test, CSRT: Choice Stepping Reaction Test, FES: Fall Efficacy Scale, LOS: Limit of Stability, ROM: Range of Motion test, SOT: Sensory Organization Test, STS5: Sit to Stand 5 times, TUG: Timed Up and Go; DT: Decision Tree, ELM: Extreme Machine Learning, KNN: K-Nearest Neighbor, MC: Majority Classifier, NB: Naïve Bayesian, RF: Random Forest, SVM: Support Vector Machine; Sens: Sensitivity, Spec: Specificity.

Another important advantage of our developed fall risk assessment system is the ability to diagnose potential fall risk factors for older individuals at high fall risks. The combination of Kinect-based multifactorial test battery and a large sample of older people (N > 100) allowed us to quantitatively evaluate the performance of the older individual on each fall risk factor. By comparing individual performance data with a normative database of older participants, each individual's deficiencies and potential fall risk factors can be easily identified [30]. This type of diagnostic report (Fig. 6) can provide a good reference for doctors to conduct in-depth examinations and design tailored fall intervention programs to effectively reduce the fall risks.

## 4.3. Limitations

This study has some limitations. First, the sample in this study was based on convenience sampling rather than random sampling, and the direct application of the main findings should be cautious. Second, due to technical limitations, the Kinect-based multifactorial fall risk assessment focuses on intrinsic risk factors rather than extrinsic factors (e.g., environmental hazards), although extrinsic factors are also important causes of falls. Last but not least, how to link the Kinect-based fall risk assessment and risk factor diagnosis to Kinect-based tailored intervention programs should be further studied.

# 5. Conclusion

This study developed a low-cost, markerless multifactorial fall risk assessment system for older people using a Microsoft Kinect v2. A Kinect-based test battery consisting of seven subtests (SOT, LOS, STS5, TUG, ROM, CSRT, and FES) was designed to comprehensively assess major fall risk factors on physiological, psychological, and integrated functions. A follow-up experiment was conducted with 102 community-dwelling Korean older women (22 in high fall risk group and 80 in low fall risk group based on their prospective fall occurrences) to assess their fall risks. Experimental results showed that the high fall risk group performed significantly worse on the Kinect-based test battery, especially in STS5, CSRT, and FES tests. Random forest classification models were further constructed to classify fall risk based on 10 significant outcome measures from the test battery with 1-year fall history. The classification model can achieve average classification accuracy of 84.7% with 83.3% sensitivity and 86.1% specificity. Furthermore, an individual's performance on the test battery was computed as the percentile value of a normative database so that deficiencies can be clearly visualized and targeted for intervention. The findings from this study indicate that the developed low-cost, markerless Kinect-based multifactorial fall risk assessment system can not only accurately and conveniently screen out ‘at risk’ older individuals, but also identify potential fall risk factors for effective interventions. The developed system has good potential for effective fall intervention and prevention.

# Abbreviations

CSRT: Choice Stepping Reaction Test; FES: Fall Efficacy Scale; LOS: Limit of Stability; ROM: Range of Motion test; SOT: Sensory Organization Test; STS5: Sit to Stand 5 times; TUG: Timed Up and Go

# Declarations

### Ethics approval and consent to participate

This study was performed in accordance with the principles of the Declaration of Helsinki and was approved by KAIST Institutional Review Board (IRB No: KH2020-015). Each participant gave the written informed consent prior to participation.

### Consent for publication

Not applicable

### Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

### Competing interest

The authors declare that they have no competing interests.

### Funding

This work was supported by the ICT R&D innovative voucher support program supervised by the Institute for Information & communications Technology Promotion (IITP20210019800012003) and the Basic Science Research Program through the National Research Foundation of Korea (NRF2017R1C1B2006811).

### Authors' contributions

TK designed experiment, acquired experimental data, performed statistical analysis, and drafted the manuscript. XY assisted on statistical data analysis. SX conceived and designed the study, obtained the funding, and reviewed and edited the manuscript draft. All authors read and approved the final manuscript.

### Acknowledgments

Authors would like to thank ‘Milmaru welfare town’ and ‘Chung-cheong bukdo sliver welfare center’ for helping recruit older subjects and providing space for experimentation. We also thank all volunteer participants for their active participation and cooperation in this experiment.

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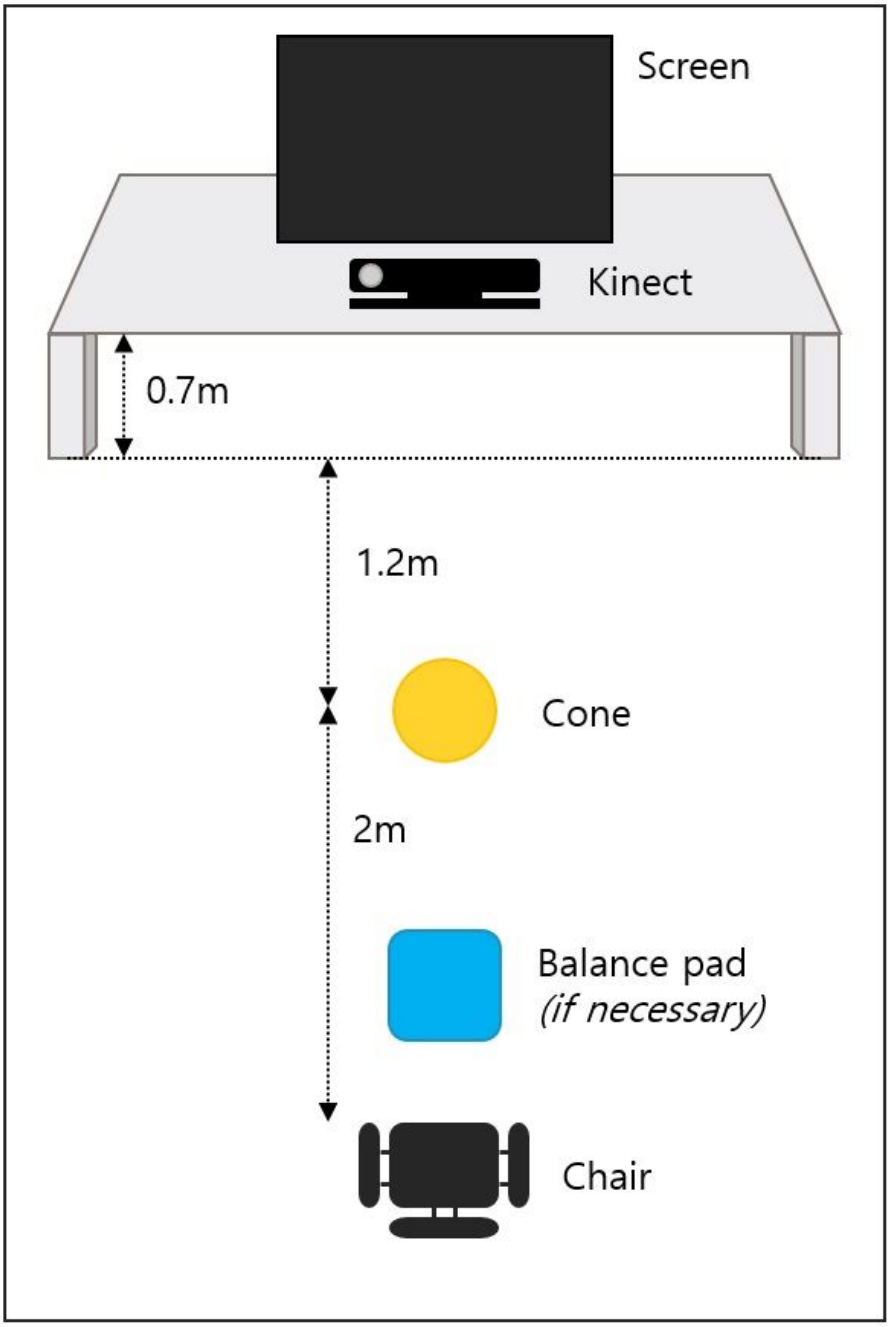
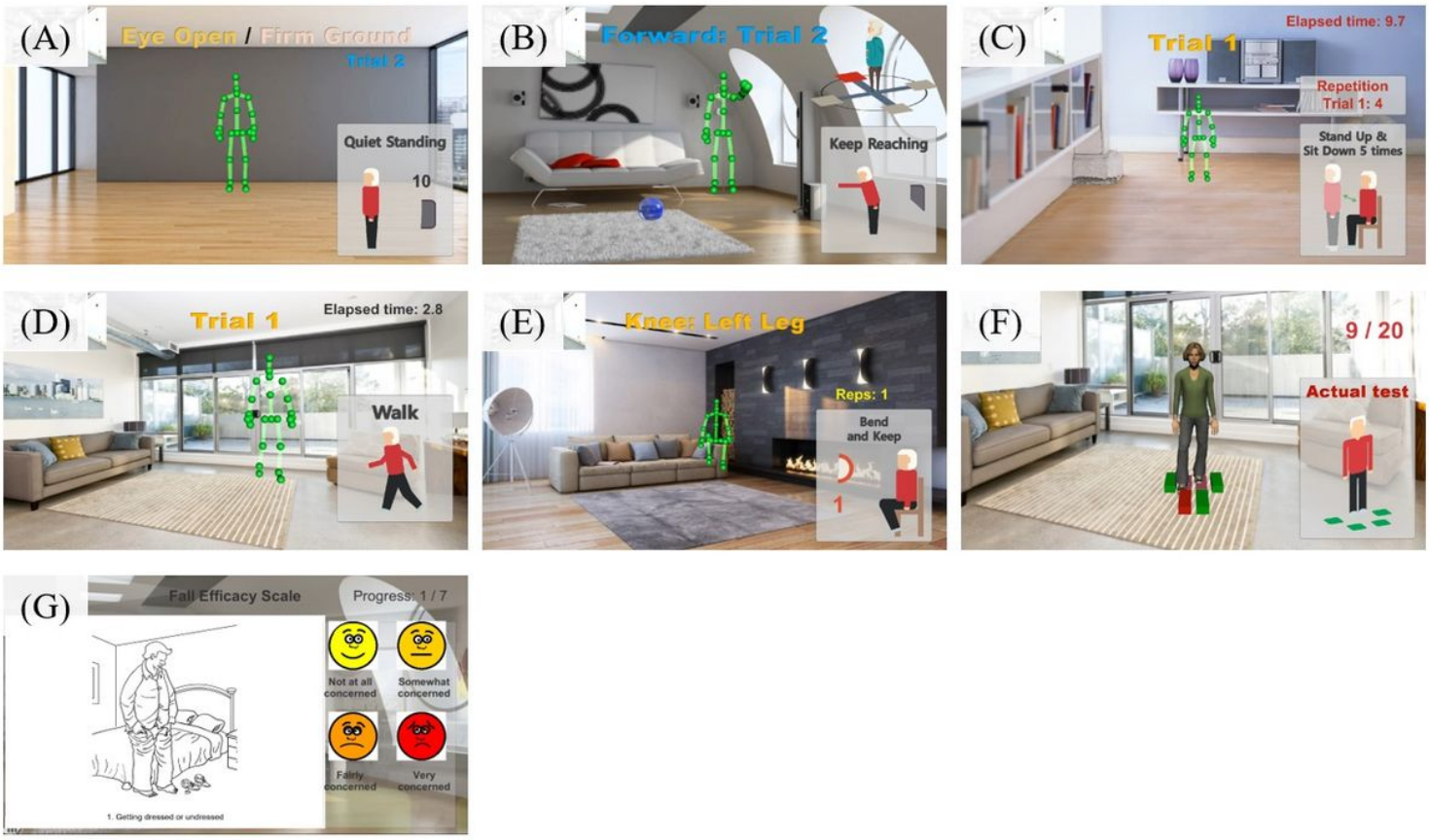
## Figures



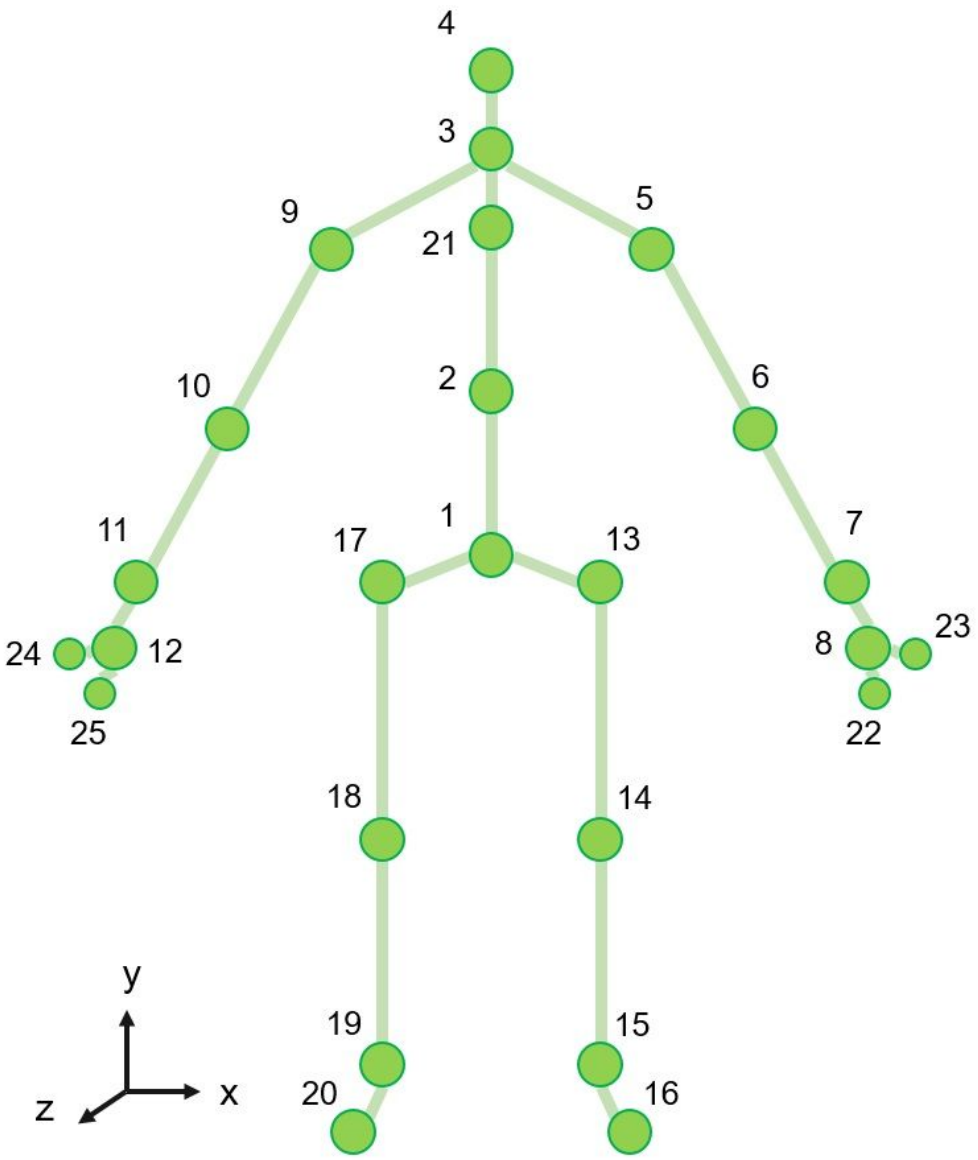
## Figure 1

The Kinect-based system setup




## Figure 2

A Kinect-based multifactorial test battery for fall risk assessment: (A) Sensory Organization Test-SOT, (B) Limit of Stability-LOS, (C) Sit to Stand 5 times-STS5, (D) Timed Up and Go-TUG, (E) Range of Motion-ROM, (F) Choice Stepping Reaction Test-CSRT, (G) Short Fall Efficacy Scale-FES.




| | |
|---|---|
| 1 | Spine Base |
| 2 | Spine Mid |
| 3 | Neck |
| 4 | Head |
| 5 | Left shoulder |
| 6 | Left elbow |
| 7 | Left wrist |
| 8 | Left hand |
| 9 | Right shoulder |
| 10 | Right elbow |
| 11 | Right wrist |
| 12 | Right hand |
| 13 | Left hip |
| 14 | Left knee |
| 15 | Left ankle |
| 16 | Left foot |
| 17 | Right hip |
| 18 | Right knee |
| 19 | Right ankle |
| 20 | Right foot |
| 21 | Spine shoulder |
| 22 | Left hand tip |
| 23 | Left thumb |
| 24 | Right hand tip |
| 25 | Right thumb |

**Figure 3**

25 skeletal joints tracked by Kinect and their coordinate system

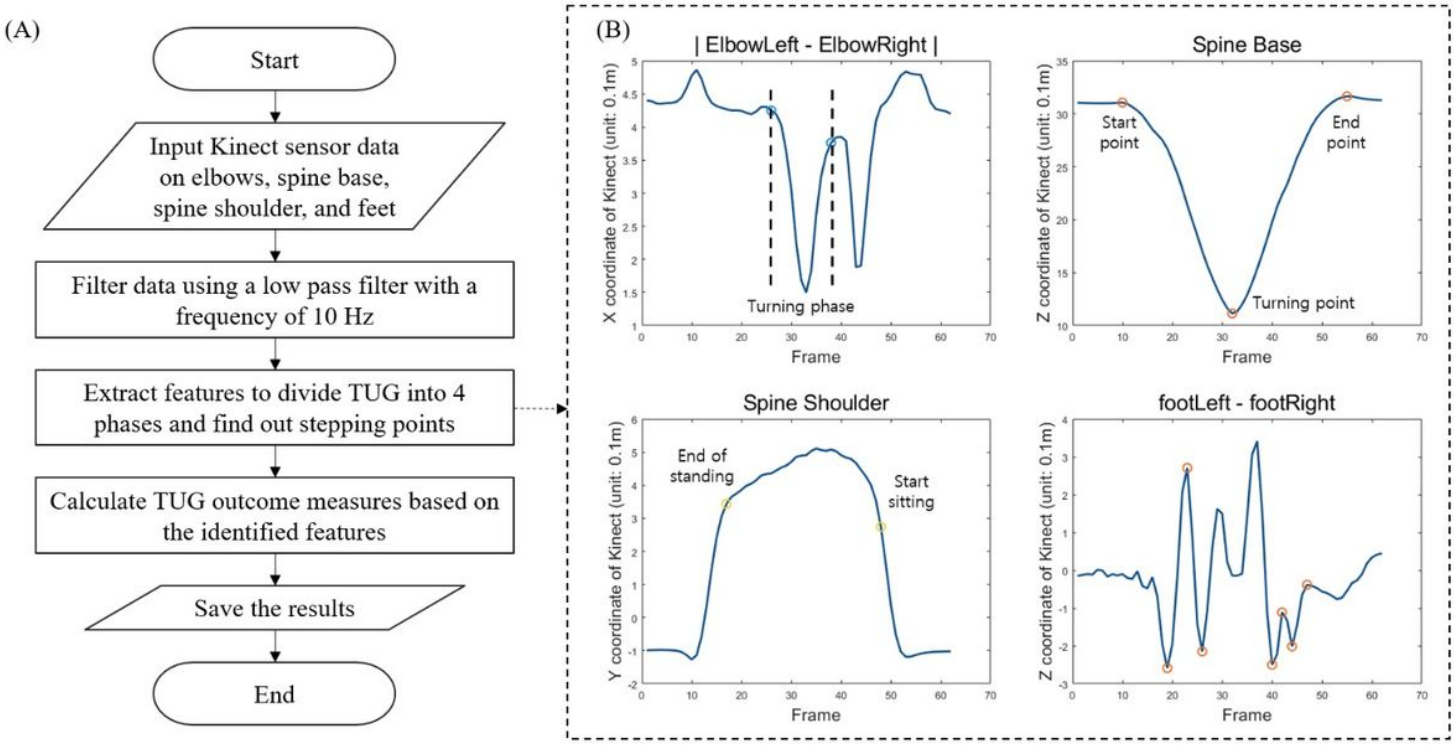



**Figure 4**

Flowchart for deriving outcome measures of TUG from Kinect sensor data (A), and automatic feature extraction for turning phase, entire TUG phase, sit-to-stand and stand-to-sit phases, and double-support moments in the gait cycle (B)

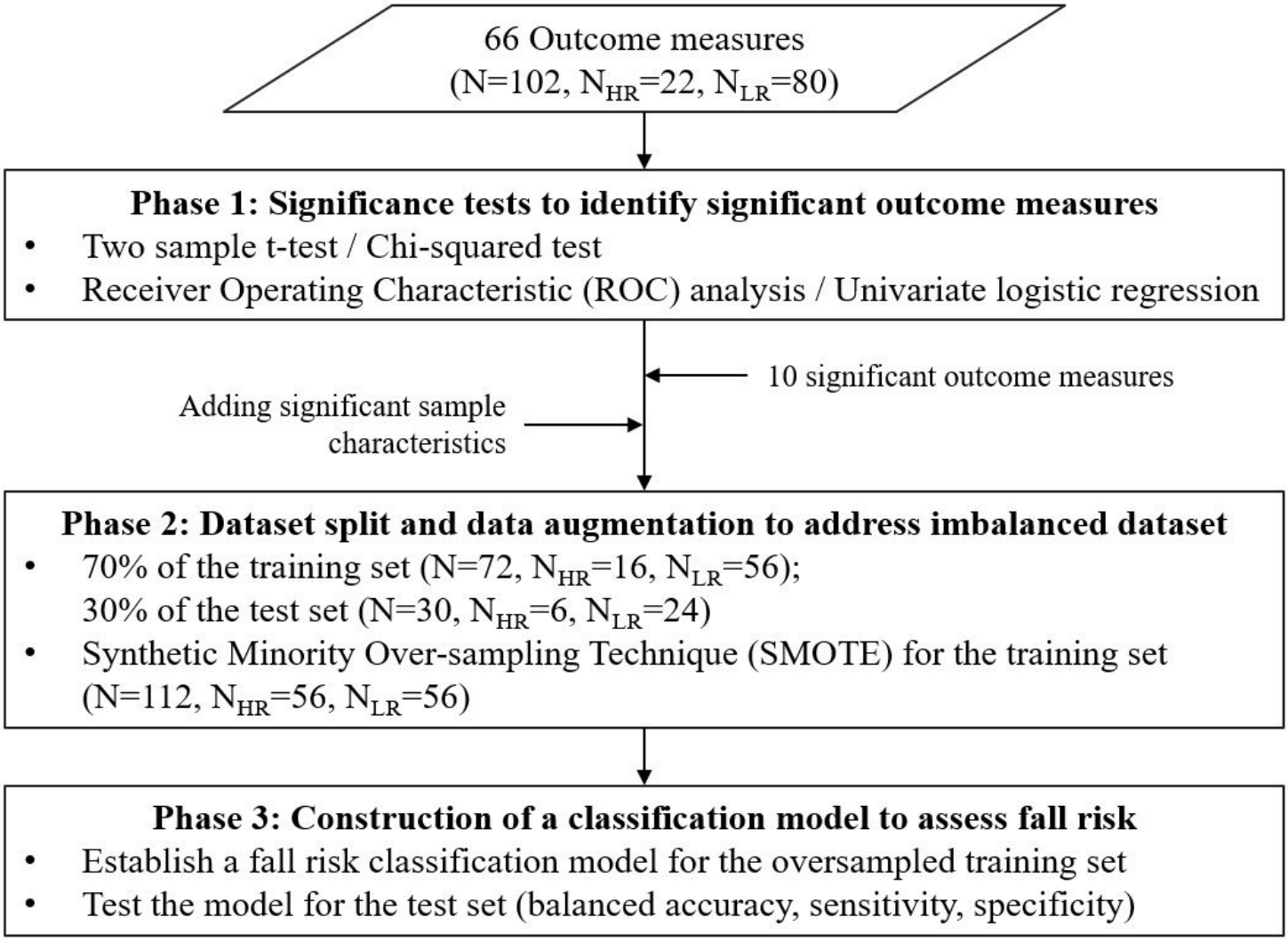



**Figure 5**

The whole process of statistical data analysis and fall risk modeling (Note: HR-High fall risk group; LR-Low fall risk group)


**Figure 6**

Typical examples of diagnostic reports for identifying potential fall risk factors: an individual with low fall risk (left) and an individual with high fall risk (right)

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixTableA1.docx