A Novel Methodology for Assessing the Fall Risk Using Low-Cost and Off-the-Shelf Devices

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***Abstract*—Early detection of fall risk can reduce health costs associated with surgery, rehabilitation, imaging studies, hospitalizations, and medical evaluations. This paper proposes a measurement-focused study oriented to evaluate a new methodology for assessing fall risk using low-cost and off-the-shelf devices. The proposed methodology consists of a data acquisition system, a data analysis system, and a fall risk assessment system. The data acquisition system is composed by a standard notebook computer and video game input devices: a Kinect, a Wii balance board, and two Wii motion controllers. The data analysis system and the fall risk assessment system, in turn, use signal processing, data mining, and computational intelligence methods, in order to analyze the acquired data for determining the fall risk of the subject under analysis. This methodology includes six static and two dynamic tests. Experiments were conducted on a population of 37 subjects: 16 with falling background, and 21 with nonfalling background. These two groups have the same age distribution. As nonlinear binary classification techniques were used, methodologies based on confidence intervals are not applicable and then tenfold cross validation was used to estimate accuracy. Hence, such a methodology can classify the fall risk as high or low, with an accuracy of 89.2%. The proposed methodology allows the construction of low-cost, portable, replicable, objective, and reliable fall risk assessment systems.**

***Index Terms*—Fall risk assessment, functional tests, statistical classifiers.**

I. Introduction

CARRYING out the activities of daily living (ADL) in a proper way, usually needs balance and the corresponding response to external stimuli (visual, auditory, and/or proprioceptive stimuli) [1]. Limitations in motor control can lead to disabilities, increasing the fall risk. Falls are the major cause of fractures or traumatic injuries in elderly population. Approximately 30% of those over 65 years have experienced at least one episode of falling in the previous year, while 6% of these results in fractures [2]–[5]. Most falls occur during locomotion [6], because of several factors that increase fall risk, such as sedentary lifestyle, health problems, and advanced age. Hence, maintaining a high level of locomotor self-sufficiency is a key issue in the management of elderly patients [4]. Falls can have many negative consequences, not only on health but also on the economy, as these increase disease morbidity, mortality, and dependence on others in order to come through with ADL. Early detection of fall risk factors can reduce health costs associated with surgery, rehabilitation, imaging studies, hospitalizations, and medical evaluations. Documented risk factors for fall risk include muscle weakness, history of falls, gait deficits, balance deficits, arthritis, depression, cognitive impairments, and age [3], [5].

In clinical practice, fall risk can be assessed through questionnaires or functional tests, like the *Timed Up and Go* [7], *One-leg Stand* [8], *Functional Reach* [9], *Tinetti Balance Test* [10], and the *Berg Balance Scale* [11], which provides important information. However, in clinical practice, functional tests are influenced by subjective factors, such as the evaluator's experience, and the lack of correlation of objective measures, as center of pressure displacement [12]. Hence, postural laboratory studies appear to be necessary for getting objective diagnoses. Nevertheless, quantitative laboratory studies based on methods like posturography or equipment such as force platforms, require high-cost equipment, specialized and trained personnel prepared for each particular piece of equipment; they get involved in complex, time-consuming, and expensive procedures, which make their application difficult.

Recently, video game devices can be found in different applications: from sports [13], to health care [14]. The Wii Balance Board (WiiBB) is a Nintendo Wii video game console that in recent studies has shown to provide useful information about the evaluation of fall risk. Its performance is comparable with posturographs and force platforms used in laboratory studies [15]. Comparison among studies dealing with force platform posturography, Wii Balance Boards (WiiBBs), and/or Wii Motions (WiiMs) is shown in Table I.

On the other hand, the Kinect is a device that provides an RBG image and a depth image, enabling three-dimensional reconstruction of the environment. It can detect people, and generate a skeleton-based representation (see Fig. 1). Despite the fact that Kinect provides information that is complementary to the center of pressure and weight, as well as the accelerations, provided by the Wii Balance Board (WiiBB) and the Wii Motion Controller (WiiM), respectively, they have not been used in an integrated fashion for estimating fall risk in elderly people with falling background.

This study aims to close the gap between clinical and laboratory tests by proposing a methodology that allows the construction of low-cost, portable, replicable, objective, and reliable fall risk assessment systems, oriented to clinical

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TABLE I
COMPARISON AMONG DIFFERENT STUDIES DEALING WITH FORCE PLATFORMS, WIIBBS AND/OR WIIMS

Focus of study	**Sensors**	**Results**
Evaluation of the potential risk of fall in elderly people with instability.	1 Translational Platform	The dynamical postural responses to destabilizing events are altered in fallers compared to non-fallers [4].
Evaluation of the standing postural control in persons with multiple disabilities.	1 WiiBB	Postural control improves among the participants [16].
Evaluation of the standing postural control in persons with multiple disabilities.	1 WiiBB	The standing postural control was improved as well as the quality of the motor response [17].
Evaluation of the standing postural control in persons with multiple disabilities.	2 WiiMs	The standing postural control was improved as well as the quality of the motor response [18].
Evaluation of the postural control for translational movements in people with developmental disabilities.	2 WiiBBs	The control over the translational movement was improved [19].
Evaluation of the postural control for translational movements in people with developmental disabilities.	3 WiiBBs	The control over the translational movement was improved [20].
Design, control and validation of training tasks and balance evaluation in older adults.	1 WiiBB	The postural control was improved [21].
Reliability of the WiiBB for evaluating impaired standing balance in persons lower limb pathology.	1 WiiBB 1 Force platform posturograph	The WiiBB is a valid tool for assessing standing balance as comparable with the standard Force platform posturograph [15].
Effectiveness of a WiiBB-based system for improving the standing balance in Acquired Brain Injury (ABI) hemiparetic patients.	1 WiiBB	WiiBB-based system represented a valid alternative to traditional treatment [22].

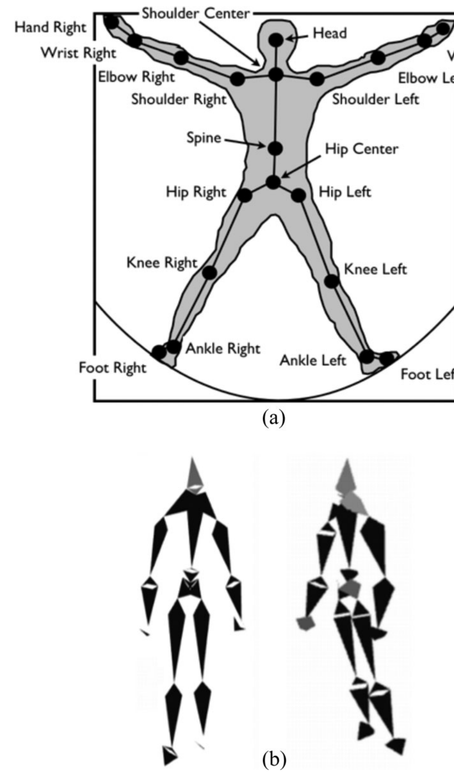

Fig. 1. Representation of the 20 joints Kinect Skeleton. (a) Diagram showing the 20 joints Kinect Skeleton. (b) Ral acquired skeleton shown from both front and side viewpoints.

practice in different populations, such as elderly people or people with musculoskeletal dysfunction. Moreover, the ability to quantitatively predict the fall risk in clinical practice is useful for preventing future falls (by controlling the evolution of the risk through exercises or continuous care), and for evaluating the use of walking aids.

Therefore, a novel methodology is used for building a scientific tool in charge of predicting the fall risk in elderly people. This methodology is based on three main systems: a data acquisition system, a data analysis system, and a fall risk assessment system. Such methodology includes eight tests that are applied to elderly people with high fall risk and low fall risk.

In this study, the participants are classified as having high fall risk or low fall risk, according to the following criterion: having at least one fall during the last year [4].

This paper is organized as follows. The methodology that was used, along with the different tests are explained in Section II, while the the acquisition process, as well as the system setup are defined and explained in Section II-A. Section II-B describes the analysis of the data, and the composition of the feature vector. In Section II-C, the implementation of the different statistical classifiers, and the selection of the most relevant features are explained. The results are presented in Section III. Finally, conclusions are drawn in Section V.

II. PROPOSED METHODOLOGY

The proposed methodology that is used to determine the fall risk class in elderly people is based on three main systems: a data acquisition system that uses a standard notebook computer and low-cost video game input devices, a data analysis system which applies signal processing, data mining, and computational intelligence methods to the acquired data, and a fall risk assessment system that uses statistical classifiers. Such methodology also includes eight tests that are applied to participants with low fall risk and high fall risk. These eight tests are composed by six static tests and two dynamic tests. The single limbstance (SLS) test, also known as the one-leg stance test or single-leg stance test, allows the balance evaluation of a subject when standing on one foot, while the double-limb stance (DLS) test is used to evaluate the balance as well, but with a subject standing on their both feet. The static tests applied to the subjects of the control group as well as the group with falling background are as follows:

1) DLS with eyes open;
2) DLS with eyes closed;
3) SLS with eyes open (standing on right foot);
4) SLS with eyes closed (standing on right foot);
5) SLS with eyes open (standing on left foot);
6) SLS with eyes closed (standing on left foot);

While the dynamic tests applied to both groups are:

7) Stepping test on the place with eyes open;
8) Stepping test on the place with eyes closed.

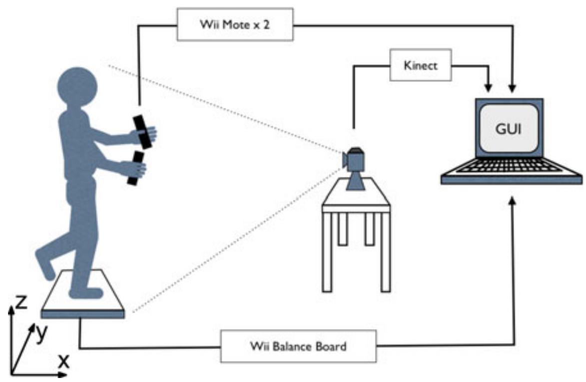

Fig. 2. Setup of the data acquisition system. Two Wii Motion hand controllers, one Wii Balance Board, and one Kinect camera are connected to a personal computer, which has the software for data acquisition, calibration, and storage.

All eight tests are performed with the subject standing on the WiiBB, in front of the Kinect, and holding one WiiM in each hand.

In the DLS test with eyes open, subjects are requested to stand upright in the WiiBB with their eyes open, and in the DLS test with eyes closed they are requested to stand upright in the WiiBB and keep their eyes closed. For the SLS tests (on each leg) with eyes open and eyes closed, subjects are asked to keep their balance, moving their arms to maintain it, if necessary. For the last two tests, i.e., stepping test on the place either with eyes open or eyes closed, subjects are requested to simulate a walk (by stepping) over the WiiBB. The number of steps required are not considered, but rather the execution time of the test.

Each subject executed these eight tests. The execution time of each of these tests has a duration of 30 s. Nevertheless, some participants finished some exercises before, as they are unable to hold the requested position, and/or started to fall down. The uncompleted assessments though, are considered inside the feature vector (see Section II-B1), as the execution time.

In this study, the low fall risk group is composed by 21 persons. All these people are Tango dancers, as they belong to a Tango Club. They dance at the Tango Club two times a week, for 2 h each time. The range of ages is between 54 and 83 years, with a mean of 68.2 years and a standard deviation (STD) of 7.2 years. The high fall risk group is composed by 16 persons from hospitals and elderly care homes with ages between 54 and 86 years. This group has a mean of 68.4 years and a standard deviation of 8.9 years.

A. Data Acquisition System

The data acquisition system is composed by one Kinect camera, one WiiBB, two WiiMs (one for each hand), and one laptop computer. All sensors are interfaced by the laptop computer: the Kinect using the USB protocol, and the WiiBB and WiiMs using the Bluetooth protocol. The setup of the system is shown in Fig. 2. The reference frame follows the right-hand rule, in which the x-axis is pointed forward, y-axis to the left, and z-axis up. Such a data acquisition system generates a set of 69 time series, as follows.

1) The Kinect camera acquires the position (x, y, z), in meter, of a person as a 3-D skeleton-like representation of 20 joints (see Fig. 1), at a sampling rate of 30 [f/s], generating 60 time series.
2) The WiiBB acquires the position of the center of pressure (x, y), in meter, and the weight w, in kilogram, at a sampling rate of 20 Hz, generating 3 times series.
3) The WiiMs acquire the corresponding accelerations (a_x, a_y, a_z) related to hands' movements, in g-force, at a sampling rate of 30 Hz, generating six time series.

Calibration of the system is needed as the information provided by the Kinect and WiiBB is not described at the same reference frame. Such calibration consists of an estimation of the position and orientation of a person standing in the WiiBB with open arms, before the acquisition of the data. Skeletal information is then transformed from the Kinect reference frame to the participant reference frame. Then, both skeletal and center of pressure information are referred to the WiiBB.

The wiiYourself library[1] is used for acquiring the data from WiiMs and WiiBB. The Microsoft Kinect Software Devolpment Kit (SDK)[2] is used for acquiring the skeleton data from the Kinect, and provides the functionalities to detect people in an image and generate a skeleton-based representation, which enables the straightforward use of motion analysis techniques.

The main software, implemented in C++, integrates the functions that come with both the wiiYourself library and Microsoft Kinect SDK, in order to compute the acquisition, calibration, and storing of the data. In addition, the main software includes a graphical user interface in order to guarantee an user friendly setup.

However, as the signals are acquired asynchronously, then an offline procedure is implemented in order to synchronize data, which is synchronized by storing the corresponding timestamp for every datum that is read from the three sensors. Then, data is resampled by using an interpolating spline function, ensuring the right synchronization.

The data acquisition system is cheap, portable, easy to connect, replicable, and useful for assessing fall risk in participants while they are performing the required set of tasks.

B. Data Analysis System

The data analysis processes the acquired data in order to determine the fall risk classification of the person under analysis by computing feature vectors, which are analyzed by a statistical classifier.

Because data are acquired asynchronously, they are resampled at 20 samples/s using a cubic spline, starting with $t = 0$ at the beginning of the test. As the number of samples n_s (for each sensor) is equal to the number of samples per second multiplied by the time the test is performed, which is 30 s (but it can be smaller for aborted tests), then $n_s = 20 \cdot 30\ \mathrm{s} = 600$.

The resampled data from the Kinect sensor are represented by the so-called K matrix, which contains the position (x, y, z)

[1]http://wiiyourself.gl.tter.org/
[2]http://www.microsoft.com/en-us/kinectforwindows/

of the 20 joints. The resampled data from the WiiBB are represented by the so-called B matrix, which contains the position of the center of mass, as well as the weight. Finally, the resampled data from the left and right WiiMs are represented by matrices L and R, containing the accelerations in x-, y-, and z-axes, respectively. Then, the matrices can be expressed as follows:

$$K = \begin{pmatrix} x^k_{1,1} & y^k_{1,1} z^k_{1,1} & \dots & x^k_{1,20} & y^k_{1,20} & z^k_{1,20} \\ x^k_{2,1} & y^k_{2,1} z^k_{2,1} & \dots & x^k_{2,20} & y^k_{2,20} & z^k_{2,20} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \\ x^k_{n_s,1} & y^k_{n_s,1} z^k_{n_s,1} & \dots & x^k_{n_s,20} & y^k_{n_s,20} & z^k_{n_s,20} \end{pmatrix} \tag{1}$$

$$B = \begin{pmatrix} x^b_{1,1} & y^b_{1,2} & w^b_{1,3} \\ \vdots & \ddots & \vdots \\ x^b_{n_s,1} & y^b_{n_s,2} & w^b_{n_s,3} \end{pmatrix} \tag{2}$$

$$L = \begin{pmatrix} a^l_{x1,1} & a^l_{y1,2} & a^l_{z1,3} \\ \vdots & \ddots & \vdots \\ a^l_{xn_s,1} & a^l_{yn_s,2} & a^l_{zn_s,3} \end{pmatrix} \tag{3}$$

$$R = \begin{pmatrix} a^r_{x1,1} & a^r_{y1,2} & a^r_{z1,3} \\ \vdots & \ddots & \vdots \\ a^r_{xn_s,1} & a^r_{yn_s,2} & a^r_{zn_s,3} \end{pmatrix}. \tag{4}$$

The analysis of the data includes statistical analysis (mean, median, and standard deviation over time), as well as principal component analysis and frequency analysis.

In order to reduce the dimensionality of the data, there are some standard approaches that can successfully be used. In this case, PCA was chosen as the approach for selecting the dominant orientations related to the data dispersion of the signal. Such an approach computes the covariance matrix from the data, and then applies an eigen decomposition in order to extract the principal directions of the data variation. This leads to a reduction of the dimensionality of the data, as the principal components are only taken into account, and not the whole set of data. This approach is applied to the accelerations sensed by the WiiMs, as only the principal component in the dominant direction is relevant and useful for the analysis.

On the other hand, the sliding FFT method [23] is suitable in order to analyze the temporal evolution of the fundamental frequency, amplitude, and phase from the time series. This method consists on using a mobile window that slides over the signal. A square window was chosen for the analysis. Herein, the artifacts that comes along with do not affect the detection of the maximum frequency, as it is the only frequency (maximum) that is used for the analysis. Therefore, for each window, an FFT is computed, and from each local FFT, a fundamental frequency is computed by selecting the index of the frequency component with the highest absolute value, i.e., the dominant index of the FFT. The width of the sliding window corresponds to 128 samples, which corresponds to a 6 s window width, while the step between two consecutive windows corresponds to 15 samples. This mean that the chosen sliding FFT has a temporal resolution of 1s. The parameters that define the particular sliding FFT algorithm are $\mathrm{width} = 128$, $\mathrm{step} = 15$, and $n_w = \mathrm{floor}((n_s - \mathrm{width})/\mathrm{step})$, where n_s is the number of samples and n_w corresponds to the number of windows used in the analysis. Then, the sliding FFT is defined by the following expressions:

$$\mathrm{FFT}(x)_u = \frac{1}{N}\sum_{k=1}^{N} x_k e^{\frac{2\pi \cdot i u k}{N}} \tag{5}$$

$$\mathrm{FFT}(x) = (\mathrm{FFT}(x)_1 \dots \mathrm{FFT}(x)_N) \tag{6}$$

$$\mathrm{FFT}_{\mathrm{slide}}(x) = \begin{pmatrix} \mathrm{FFT}(x_{1:\mathrm{width}}) \\ \mathrm{FFT}(x_{\mathrm{step}+1:\mathrm{step}+1+\mathrm{width}}) \\ \vdots \\ \mathrm{FFT}(x_{k\cdot\mathrm{step}+1:k\cdot\mathrm{step}+1+\mathrm{width}}) \\ \vdots \\ \mathrm{FFT}(x_{n_w\cdot\mathrm{step}+1:n_w\cdot\mathrm{step}+1+\mathrm{width}}) \end{pmatrix}. \tag{7}$$

The sliding FFT procedure is used over the principal components of the WiiMs, the y-component of the center of mass, and the x-component of the left and right knees acquired by the kinect in order to compute the evolution of the fundamental frequency, amplitude, and phase over time. For this application, the fundamental frequencies are expected to be between 0.7–2 Hz. Such a range of frequencies usually belong to the stepping in the place activity.

Besides, mean, median, and standard deviation are applied not only to the data acquired by the Kinect and WiiBB, but also to the dimensionality-reduced data acquired by the WiiMs. Furthermore, statistical analysis was also applied to the frequency-related signals as well.

The analysis of the data is represented by Fig. 3, where mean, median, and standard deviation are computed for the signals from the Kinect, the WiiBB, and the principal component from the WiiMs. Moreover, sliding FFTs are computed for signals from the WiiBB, the principal components of the WiiMs, and the x-component of both knees of the Kinect. Then, this information is used for computing a feature vector. As a result, a set of feature vectors is generated, and used as the training data for the classification.

1) Feature Vector: The processed data, as shown in Fig. 3, determines the composition of the feature vector, which is fed into the statistical classifier. The classifier is in charge of determining the class of the data: high or low fall risk.

The criterion for selecting the initial set of features is not based on an expert-based preliminary analysis, but based on the selection of a large number of features as possible candidates, no matter possible redundancies among each other.

Depending on the nature of the tests, static or dynamic, different features are considered. However, not all the information

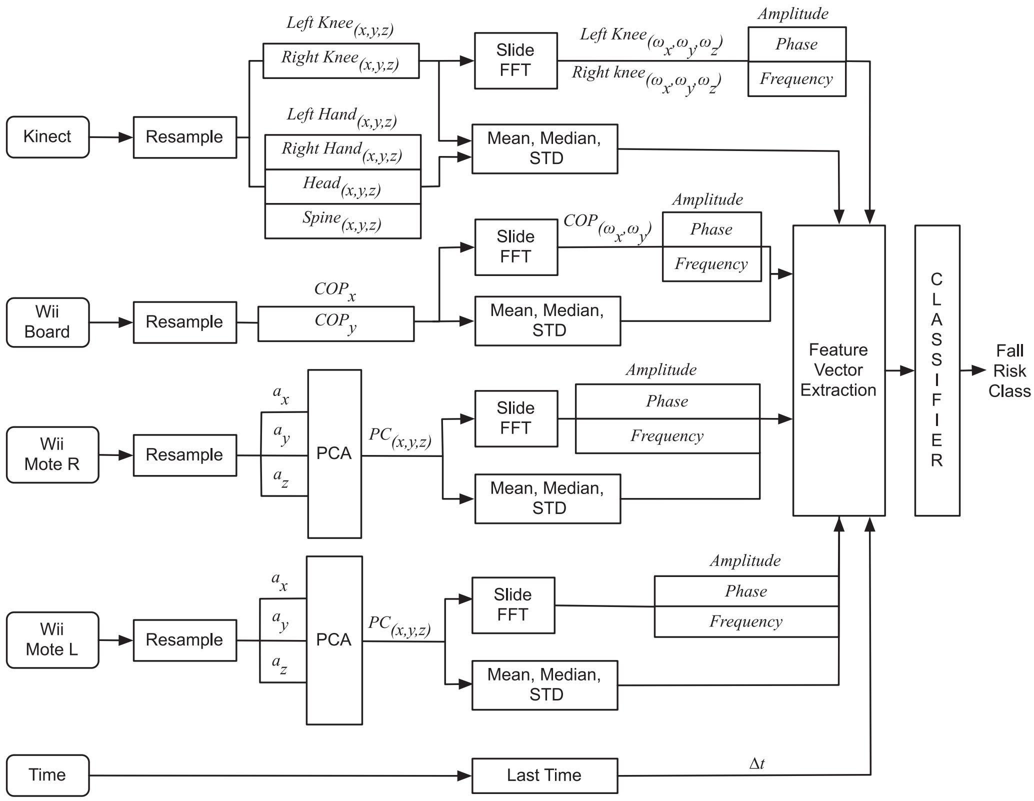

Fig. 3. Diagram of the computations performed on the data from the sensors. The coordinates of the center of pressure (cop_x, cop_y), the acceleration vector (a_x, a_y, a_z), and the principal component $\mathrm{PC}_{(x,y,z)}$ of a given signal.

TABLE II
LIST OF FEATURES FOR STATIC TESTS

Parameter	Device	Characteristic
Mean, Median, STD	WiiBB	Pressure point (x, y axes)
Mean, Median, STD	WiiBB	Pressure point's absolute value (x, y axes)
STD	WiiM	Accelerations' principal component (both hands)
Time	Chronometer	The execution time of the test

regarding the 20 joints from the Kinect device was taken into account for the analysis. Only the data from the knees, head, hand, and spine joints were selected, as they provide the most suitable information about assessing the risk of fall [24].

In the case of the static tests, the features are considered by selecting the attributes listed in Table II. The number of features for each static test becomes 15. Then, the total number of features becomes 90 (15 $\times$ 6).

In the case of the dynamic tests, the features are considered by selecting the attributes listed in Table III. Please note that the frequency analysis is based upon a sliding window of 6 s.

The number of features for each dynamic test becomes 71. Then, the total number of features, due to dynamic tests becomes 142 (71 $\times$ 2).

Therefore, the total number of features conforming the feature vector is then the sum of all the features corresponding to the static (90) and dynamic (142) tests, i.e., 232 features.

C. Fall Risk Assessment System

The fall risk assessment system is used in order to determine the fall risk in elderly people. The system is built using statistical classifiers, which are trained and validated using the data of subjects with falling background and nonfalling background. Thus, these data are used for adjusting the parameters of the classifiers in the training phase, and for testing them in the evaluation phase.

In the training phase, the training dataset is represented by the feature vector. It contains the information regarding the attributes extracted from a control group that has low fall risk, as well as another group that has falling background. The resulting dataset is then used for training the statistical classifiers in order to determine the fall risk class.

In the next phase, i.e., the evaluation phase, the *k*-fold cross-validation method is used for the classification accuracy estimation [25]. In order to compute the evaluation, $k = 10$ was chosen. This method, at the beginning, computes only one random permutation of the training dataset. Then, the training dataset is partitioned into ten subsets. Of these ten subsets, one subset is retained as the validation data for testing the classifier (this subset is called the ”testset”), and the remaining nine subsets together are used as the training data (”trainset”). Then, a classifier is trained on the “trainset” and its accuracy is evaluated on the “testset.” This operation is repeated ten times. Therefore, the resulting accuracy estimation of the classifier is the average of all the accuracy estimations obtained after each iteration.

TABLE III
LIST OF FEATURES FOR DYNAMIC TESTS

Parameter	Device	Characteristic
Mean, Median, STD	WiiBB	Pressure point's amplitude (y axis)
Mean, Median, STD	WiiM	Accelerations' principal component amplitude of the left and right hand
Mean, Median, STD	WiiM	Phase difference between the accelerations' principal component of the left and right hand
Mean, Median, STD	WiiBB/WiiM	Phase difference between the pressure point (y axis) and the accelerations' principal component of the left hand
Mean, Median, STD	WiiBB/WiiM	Phase difference between the pressure point (y axis) and the accelerations' principal component of the right hand
Mean, Median, STD	WiiM	Error of the fundamental frequency between the accelerations' principal component of the left and right hand
Mean, Median, STD	WiiBB/WiiM	Error of the fundamental frequency between the pressure point (y axis) and the accelerations' principal component of the left hand
Mean, Median, STD	WiiBB/WiiM	Error of the fundamental frequency between the pressure point (y axis) and the accelerations' principal component of the right hand
Mean, Median, STD	Kinect	Amplitude difference between the left and right knees' movement (x axis)
Mean, Median, STD	Kinect	Amplitude of the left knee's movement (x axis)
Mean, Median, STD	Kinect	Amplitude of the right knee's movement (x axis)
Mean, Median, STD	Kinect	Absolute amplitude difference between the left and the right knees' movement (x axis)
Mean, Median, STD	Kinect	Amplitude difference between the left and right knees' movement divided (element-wise) by the sum of both amplitudes (x axis)
Mean, Median, STD	Kinect	Absolute amplitude difference between the left and right knees' movement divided (element-wise) by the sum of both amplitudes (x axis)
Mean, Median, STD	Kinect	Phase difference between the left and the right knees' movement (x axis)
Mean, Median, STD	Kinect	Spine point's movement (y axis)
Mean, Median, STD	Kinect	Head point's movement (y axis)
STD	Kinect	Left and right hand points' movement (y axis)
Mean, Median, STD	WiiBB	Pressure point (x, y axes)
Mean, Median, STD	WiiBB	Pressure point's absolute value (x, y axes)
STD	WiiM	Accelerations' principal component of the left and right hand
Time	Chronometer	The execution time of the test

In order to determine the evaluation accuracy of the classification, this method was applied to the whole set of features vector. Besides, this method was also applied to a reduced set of features.

1) Feature Selection Algorithm: In order to improve the fall risk analysis, a reduced set of features was selected. Such a subset of features are important as they improve the accuracy of the classification. The main assumption here is that data may contain many redundant or irrelevant features. These features do not provide neither additional nor useful information. Usually, feature selection algorithms are used when there is a large number of features in comparison to few samples.

In this particular case, in which there are 232 features for training the classification of 37 subjects, it is important to reduce the number of features, in order to get a higher classification accuracy. Then, an attribute selection was conducted. Such a selection was performed by using the info gain attribute evaluator along with the ranker search method, both implemented in Weka package [26]. In a nutshell, such approach evaluates the worth of an attribute by measuring the information gain with respect to the class. Actually, it measures the difference between the entropy of the class and the average entropy of the class given an attribute. Then, those features with the highest discrimination power are ranked and selected.

2) Statistical Classifiers: Four classifiers, used to predict the falling risk class, were implemented in Weka package [26]. These four classifiers are as follows.

1) The Naïve Bayes as a linear classifier [27], which is based on assuming that each feature is statistically independent given a certain class.
2) The locally weighted learning (LWL) classifier [28], which is based on selecting the nearest neighbor samples over the dataset, in order to train a classifier. In this particular case, the decision stump classifier was used.
3) The AdaboostM1 classifier [29], which corresponds to a nonlinear mixing classifier composed by weak subclassifiers, each being a threshold-based classifier applied to one component of the data at a time.
4) The Dagging classifier [30], which corresponds to a meta classifier that creates a number of disjoint subsets. Each subset is used to train a base classifier. Then, predictions are made by a majority vote among the base classifiers.

All these four classifiers were trained not only for each of the tests, but also considering the whole set of tests along with whole set of features vector. Moreover, these classifiers were also trained by using a subset of the most representative features. Then, the four classifiers were evaluated, for either the whole set of feature vectors or the reduced set of features, and the fall risk class was predicted.

III. RESULTS

The classification accuracy rate was estimated by using tenfold cross validation on the available data. The accuracy rates, according to the four classifiers, either for each test or all test as a whole (along with all the features) are shown in Table IV.

As stated in Section II-C1, not all of the attributes have the same importance for classification. In fact, taking into account the whole set of features can deteriorate the performance of the classifiers, as many irrelevant features are considered. Therefore, by using the info gain attribute selector (explained in Section II-C1), a reduced set of features was obtained by selecting only the attributes that generate an information gain value greater than zero. This subset corresponds to 12 features. In order of importance, the selected attributes are shown in Table V.

Therefore, by considering only these 12 features, the accuracy rates according to the four classifiers are reported in Table VI.

TABLE IV
ACCURACY RATES INCLUDING ALL FEATURES

Test	Dagging	AdaboostM1	Naïve Bayes	LWL
DLS with eyes open	53.8%	30.8%	43.6%	43.6%
DLS with eyes closed	61.5%	64.1%	53.8%	51.3%
SLS on right foot with eyes open	68.4%	63.2%	60.5%	68.4%
SLS on left foot with eyes open	68.4%	71.1%	71.1%	57.9%
SLS on right foot with eyes closed	52.6%	57.9%	55.3%	60.5%
SLS on left foot with eyes closed	47.4%	60.5%	57.9%	65.8%
Stepping test on the place with eyes open	64.1%	41%	59%	53.8%
Stepping test on the place with eyes closed	63.2%	65.8%	63.2%	63.2%
All tests (features from all tests)	48.6%	70.3%	59.5%	78.4%

In order to describe the distribution of the data in more detail, additional descriptive measures are reported. Accordingly, the data distribution of the 12 most discriminative features are expressed through the median and the 25th and 75th percentiles for high and low risk class, as shown in Fig. 4. Furthermore, the three most important features, among these 12, are plotted in a 3-D graph, as shown in Fig. 5.

IV. DISCUSSION

By analyzing the obtained results, it can be observed that the SLS tests with eyes open are the most discriminative ones. Notice that on the left foot, AdaboostM1 and Naïve Bayes classifiers give higher accuracy rates compared with the tests on the right foot, while the LWL classifier decreases, and the Dagging classifier remains the same.

Another discriminative test is the stepping test on the place with eyes closed. It is observed here that the four classifiers have similar accuracy rates; three of them have an accuracy rate of 63.2%, while the AdaboostM1 classifier has 65.8%. These rates, in three of the four classifiers, are higher than the ones belonging to the stepping test on the place with eyes open. Notice that in the case of the Dagging classifier, the accuracy rate is only slightly slower; it decreases from 64.1% to 63.2%.

Considering the SLS tests with eyes closed, the LWL classifier gives the best accuracy rates among the other classifiers, i.e., 60.5% against the 52.6% (Dagging) for right foot, and 65.8% against 47.4% (Dagging) for left foot.

According to the results obtained for the DLS tests, only the accuracy rates belonging to the DLS test with eyes closed could be considered as relevant, i.e., 61.5% (Dagging) and 64.1% (AdaboostM1), while the DLS test with eyes open definitely provide nonsignificant information in the studied population.

TABLE V
SUBSET OF 12 FEATURES

Parameter	Device	Characteristic	Test
STD	WiiBB	Pressure point (y axis)	SLS on left foot with eyes open
STD	WiiBB	Pressure point's absolute value (y axis)	SLS on left foot with eyes open
Mean	WiiBB/WiiM	Phase difference between the pressure point (y axis) and the accelerations' principal component in the right hand	Stepping test on the place with eyes closed
STD	WiiBB	Pressure point (x axis)	SLS on left foot with eyes open
STD	WiiBB	Pressure point (x axis)	SLS on right foot with eyes open
STD	WiiBB	Pressure point's absolute value (y axis)	SLS on right foot with eyes closed
STD	WiiBB	Pressure point's absolute value (y axis)	SLS on left foot with eyes closed
Median	WiiBB	Pressure point (x axis)	Stepping on the place with eyes closed
Mean	WiiBB	Pressure point (x axis)	Stepping on the place with eyes open
STD	WiiBB	Pressure point (y axis)	SLS on right foot with eyes closed
Median	WiiBB	Pressure point (x axis)	Stepping on the place with eyes open
Median	WiiBB	Pressure point's absolute value (x axis)	SLS on right foot with eyes open

TABLE VI
ACCURACY RATES WITH THEIR STD, CONSIDERING THE 12 MAIN FEATURES FROM ALL TESTS

Test	Dagging	AdaboostM1	Naïve Bayes	LWL
All tests	89.2%	78.4%	81.1%	64.9%
	STD: 16.2%	STD: 21.5%	STD: 20.4%	STD: 24.8%

Considering all tests together (and the whole set of features) do not give better results than considering each test separately, as decreasing the accuracy rate for three of the four classifiers, except in the case of the LWL classifier, in which its accuracy rate raises up to 78.4%. This result can suggest that only for the LWL classifier, the two classes are well defined in the full feature space.

Considering only the 12 selected features, the classification accuracy is raised for three of the four classifiers (see Table VI). Notice that for the Dagging classifier, the accuracy was raised from 48.6% to 89.2%. Note that among these 12 features, the ones related to the WiiBB give more discriminative power when classifying the falling risk. However, other features, that are related to the WiiMs, can also be discriminative for classification,

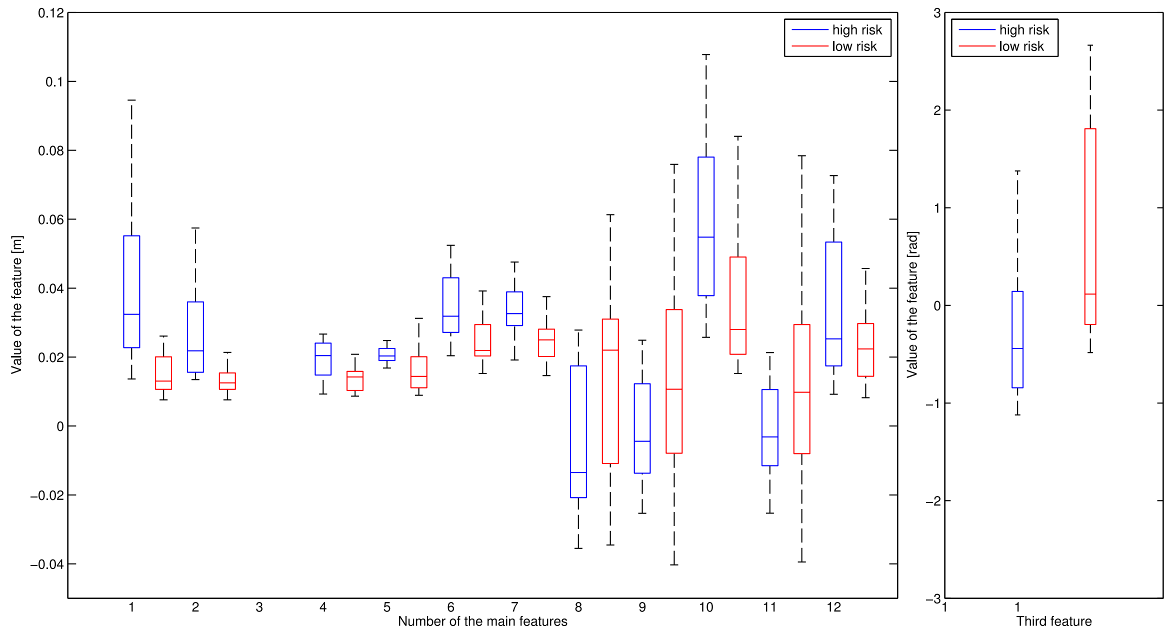

Fig. 4. Box plot of 12 selected features for high and low risk class.

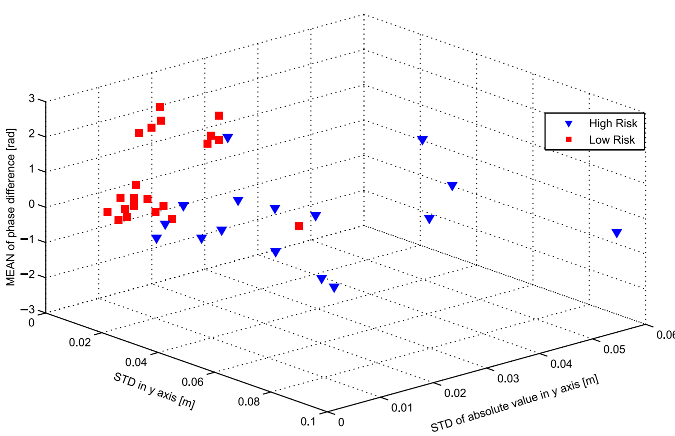

Fig. 5. Distribution of high (blue) and low (red) fall risk classes, taking into account only the three most representative features.

i.e., the phase difference between the pressure point of the WiiBB, in the y-axis, and the accelerations' principal component of the WiiM in the right hand for the stepping test on the place with eyes closed. Definitely, the features related to the Kinect device give nonsignificant information for classification. Nevertheless, the Kinect gives important information related to the movements of the upper and lower limb, no matter their related features, though were not selected as important.

As shown in Fig. 4, it is clear how the distribution of the data have different distributions for high and low fall risk. As expected, for the two main features, the data dispersion in high fall risk is higher than in low fall risk. Besides, for the third most discriminative feature in low fall risk class, its median is closed to zero.

The three most important features are plotted in a 3-D graph, as shown in Fig. 5. Notice that data near the ideal classification hyperplane are not correctly classified because high risk distribution and low risk distribution have a small overlap in the feature space. Moreover, there is an isolated low risk datum inside the high risk data. This datum was not considered as an outlier.

V. Conclusion

Low-cost and off-the-shelf devices, designed for home video game, provide valuable information about assessing human fall risk. The proposed setup uses these devices in an integrated fashion. A data acquisition system provides a graphical user interface for enabling the selection of a test to be computed by a participant. The data analysis and assessment toolbox use a defined set of feature vectors for training statistical classifiers, in order to estimate fall risk among elderly people.

The proposed methodology is more effective when all tests are considered for classification. However, taking into account all the features is not as effective as selecting the most discriminative ones. Indeed, by considering only a reduced set of representative features, the accuracy rates were improved in three of the four classifiers.

According to the reduced set of features, the Kinect device does not give significant information about the fall risk classification. Although, kinematic information is also valuable when analyzing the movement of the participants.

On the other hand, the WiiBB is the device for which almost all the features are referred to. Therefore, this device is the most important when selecting discriminative attributes. In fact, the most important feature deals with the estimation of the center of pressure. However, when WiiBB is used along with the WiiMs, as working together in an integrated fashion, they give valuable and relevant information, giving further robustness to the system.

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