Fall Risk Prediction via Classification of Lower Extremity Strength in Older Adults with Exergame-Collected Data

Hagen Becker[1], Augusto Garcia-Agundez[1], Philipp Niklas Müller[1], Thomas Tregel[1], André Miede[2] and Stefan Göbel[1]

[1] Multimedia Communications Lab, Technische Universitaet Darmstadt, Darmstadt, Germany

[2] HTW Saar, Saarbruecken University of Applied Sciences, Saarbruecken, Germany

Corresponding author: Augusto Garcia-Agundez, Multimedia Communications Lab, TU Darmstadt, Rundeturmstr. 10, 64283 Darmstadt, Germany. Augusto.garcia@kom.tu-darmstadt.de

Abstract. Objective: The goal of this article is to present and evaluate a sensor-based falling risk estimation system. The system consists of an array of Wii Balance Boards (WBB) and an exergame that estimates if the player is at an increased falling risk by predicting the result of the 30 Second Chair-Stand Test (30CST). **Methods**: 16 participants recruited at a nursing home performed the 30CST and then played the exergame as often as desired during a period of two weeks. For each session, features related to how they walk and stand on the WBBs while playing the exergame were collected. Different classifier algorithms were used to predict the result of the 30CST on a binary basis (able or unable to maintain physical independence). **Results**: We achieved a maximum accuracy of 91% when attempting to estimate if the player's 30CST score will be over or under a threshold of 12 points using a Logistic Model Tree. We also believe it is feasible to predict age- and sex-adjusted cutoff scores. **Conclusion**: An array of WBBs seems to be a viable solution to estimate lower extremity strength and with it the falling risk. In addition, data extracted while playing may form a basis to perform a general screening to identify elderly at an increased falling risk.

Keywords. Wii Balance Board, Fall Risk, Fall Detection, Balance, Exergames, Serious Games

Introduction

Among older adults, falls are an important cause of mortality and early placement in nursing homes. The main causes of falls are accidental and environment-related (31%) or caused by gait imbalances (17%). Approximately 30 to 60% of older adults fall each year. Out of these falls, 10 to 20% result in injury, hospitalization, or death. Among the most relevant factors to prevent these falls are risk assessment and exercise [1]. The role of sensor-based solutions in regards to falling risk has traditionally been focused on detecting said falls. Both wearable and smartphone-based solutions for fall detection are readily available [2].

In the field of training and health, exergames, active video games that incorporate physical movements, aim to combine physical exercise with the fun associated with gaming. The main advantage of this approach is that it increases motivation and thus adherence to training [3]. In addition, designing games that perform fall risk prevention exercises or collect clinically meaningful data in the background, using sensors similar to the ones already used to detect falls, is a positive factor [4]. An additional advantage of this approach, in comparison to traditional exercise, is the possibility to adapt the exergame to the specific needs of the user in real time and without external intervention based on game data [5].

The possibility of using the Wii Balance Board (WBB) to estimate whether the player is at an increased falling risk has been identified [6]. However, related publications mention the need for additional studies, particularly in finding direct relationships between sensor data and clinically meaningful falling risk estimation methods. Studies show that WBB data contain information that allow a discrimination between elderly who previously fell and others who did not [7]. This study achieved an accuracy of 76.6% in this binary classification on 12 participants. Early evidence also shows that the WBB could be used to train balance in the elderly [8], and that there are statistically significant differences in the way elderly at falling risk interact with the WBB. These differences actually correlate with clinical fall risk tests. Yamada et al.[9] found statistically significant differences and moderate correlations (r=0.69) in a study with 45 participants. A limitation of the WBB is that, due to its small surface, it can only be used to estimate balance while standing, and not in movement.

In a previous article, we presented PDDanceCity, a city map exergame with the goal of providing dual-tasked cognitive and physical rehabilitation [10]. The game is controlled with an array of six WBBs, which we call Extended Balance Board (EBB) [11]. Thanks to its extended surface, EBB data can be used to estimate the balance of the player both while standing and walking. We believe the data extracted from the EBB could be used to estimate the balance and gait skills of the player in the background, without the need to actively perform any specific test, or for any caregiver to be present.

In order to do so, this study aims to analyze the possibility of training a classifier to predict the falling risk of a player based on EBB data collected in the background while playing PDDanceCity. This can be achieved by attempting to predict the score of a standardized test that can be used to assess the falling risk. There are several such tests to measure lower extremity strength, for example, the 30 second Chair-Stand test (30CST) [12], which is part of the Fullerton Fitness Test Battery, and is fairly easy to administer. The Fullerton Fitness Test Battery is commonly employed in older adults in community settings and can measure physical patterns of physical decline in advanced ages. Evidence suggests it could also be used as a screening test to estimate the falling risk and balance impairment in older adults [13, 14]. The 30CST classifies participants as subjects able or unable to maintain physical independence depending on whether their test score is above or below an age- and sex-adjusted cutoff. We believe this binary prediction could be achieved with a classifier algorithm using data extracted from the EBB.

Thus, the goal of this study is to determine the feasibility of classifying EBB-extracted data to perform a binary prediction (player is able or unable to maintain physical independence). This prediction could be used to detect when residents at an elderly nursing home may be losing physical indepencend and could be more likely to fall in the near future. We validate this estimation basing the result on a prediction of the 30CST score. Data is collected while users are playing PDDanceCity to provide a very simple background screening process determining whether the player may be at an increased falling risk.

Methods

PDDanceCity [10] is a labyrinth navigation exergame designed for dual-tasking rehabilitation. The goal of the game is to navigate a labyrinth, representing a city map to reach a goal, where only two-dimensional movements are possible (up, down, right and left). As an additional requirement, players are encouraged to reach the target with the least possible number of steps. In addition, they may be required to visit a given number of points of interest (for example a museum, monument or café) which may or may not be directly on the shortest path (Figure 1). The game offers a dual-tasking rehabilitation task, training visuospatial function, memory, balance, and physical coordination.

PDDanceCity is controlled with system consisting of an array of six WBBs, called EBB [11] (Figure 2). A controller receives all data from the WBBs and forwards it via a USB connection to a PC. Information sent through the USB interface contains the board identifier (ID), based on its MAC address, as well as the current value of each of its weighing sensors (four per WBB, for a total of 24). The refresh rate per board is 20 Hz.

In order to use EBB data as a basis to control PDDanceCity, the center of mass $\boldsymbol{com}(t)$ is calculated as follows. We define $\boldsymbol{S}$ as the 6x4 matrix of sensor values (six WBB boards and four sensors per board), and $s_{\mathrm{i,j}}(t)$ as the value of sensor (i, j) of $\mathbf{S}$ in instant t. We define $\mathbf{C}$ as the matrix of (x, y) coordinate vectors $\boldsymbol{c}_{\mathrm{i,j}}$ assigned to each sensor (Figure 3), based on its position. We also define $w(t)$ as the last total weight value calculated by all boards, that is, the weight of the player. $\boldsymbol{com}(t)$ is calculated as the weight-normalized bidimensional projection of sensor values as:

$$\boldsymbol{com}(t) = (com_x(t), com_y(t)) = \frac{1}{w(t)} \sum_{i=1}^{6} \sum_{j=1}^{4} (s_{\mathrm{i,j}}(t)\boldsymbol{c}_{\mathrm{i,j}})$$

This results in a set of two minus one to one values (com_x, com_y) which can be used to determine intentionality. To achieve this, we define a directional intention based on two conditions: the main directional component must be equal to or greater than 0.5 in magnitude, and the other component must be equal to or lesser than 0.1 in magnitude. As an example, $(0.1, 0.9)$ represents an upwards step, and $(-0.8, 0.05)$ would represent a leftwards movement. Between each step, the player is always required to return to the center (both values lower than or equal to 0.1 in magnitude). Figure 4 represents two examples of this directional intention. We also define the instability factor $if(t)$ as an approximation of the first order differential of $\boldsymbol{com}(t)$. This parameter is a measure of how a player shifts their weight on the EBB. A very fast weight shifting, causing a high value of $if(t)$, would be an indicator of potential lack of balance (or loss thereof) among older adults who are not expected to move quickly. This is calculated as:

$$if(t) = \sqrt{\frac{1}{2}(com_x(t) - com_x(t-1))^2 + \frac{1}{2}\,(com_y(t) - com_y(t-1))^2}$$

Where $(t-1)$ represents the value prior to the most recent one t. In this manner, when $if(t)$ surpasses a certain threshold, a potential loss of balance may have occurred. For every level played, PDDanceCity stores a .xml file that includes the player's profile information, information about the level, steps taken and all values of $\boldsymbol{com}(t)$ and $if(t)$.

Finally, we extract a series of features based on $\boldsymbol{com}(t)$ and $if(t)$. These features are mostly related to average values, standard deviations and maxima and minima of $\boldsymbol{com}(t)$ under different circumstances, as well as the number of times that $if(t)$ overcame different possible thresholds. In addition to these two elements, we also consider features related to the time intervals between steps, and the standard deviation of these intervals. A complete feature list is presented in Table 1. All features are calculated per playthrough, with no windowing. We used the Matlab software to calculate these features [15].

To evaluate our system, we recruited 16 participants (median age 73, 6 males) at a nursing home in Darmstadt, Germany. A computer was installed in a common room, connected to a television and the EBB (Figure 2). Participants were invited to play PDDanceCity as often as they desired for a period of two weeks. During the first session, nominal data (age and sex) was collected, and the 30CST was administered. The resulting 30CST scores ranged between 0 and 17, with a median of 13. All sessions took place under observation of one of the authors, to ensure that no falls occurred. Otherwise, the game sessions were unsupervised. We obtained approval of the ethics committee of the Technical University of Darmstadt for this evaluation.

Table 1: System features and calculation

Features	Description	Calculation
$Com_{Avg_{Direction}}$	Average $\boldsymbol{com}$ value for movements in each direction, where $n_{COM,Direction}$ represents the number of steps for each direction. Four two-dimensional features (x,y) per playthrough	$\frac{\sum_{t=1}^{n_{COM,Direction}} \boldsymbol{com}(t)}{n_{COM,Direction}}$ $Direction = Up \leftrightarrow com_y > 0.5, \lvert com_x \rvert < 0.1$ $Direction = Down \leftrightarrow com_y < -0.5, \lvert com_x \rvert < 0.1$ $Direction = Right \leftrightarrow com_x > 0.5, \lvert com_y \rvert < 0.1$ $Direction = Left \leftrightarrow com_x < -0.5, \lvert com_y \rvert < 0.1$
$Com_{Std_{Direction}}$	Standard deviation of $\boldsymbol{com}$, for each direction, as above. Eight features per playthrough	$\sqrt{\frac{\sum_{t=1}^{n_{COM,Direction}} \left(com_i(t) - Com_{Avg_{Direction,i}}\right)^2}{n_{COM,j} - 1}}$, $i = x, y, Direction = Up, Down, Left, Right$
$Balance_{Up}$, $Balance_{Down}$	Average value of com_y for all values where $com_y > 0$ (up) or $com_y < 0$ (down), where n_{COM} is the number of $\boldsymbol{com}$ samples. Two features per playthrough	$\frac{\sum_{t=1}^{n_{COM}} com_y(t)}{n_{COM}} : com_y > 0, \frac{\sum_{t=1}^{n_{COM}} com_y(t)}{n_{COM}} : com_y < 0$
$Balance_{Right}$, $Balance_{Left}$	Average value of com_x for all values where $com_x > 0$ (right) or $com_x < 0$ (left). Two features per playthrough	$\frac{\sum_{t=1}^{n_{COM}} com_x(t)}{n_{COM}} : com_x > 0, \frac{\sum_{t=1}^{n_{COM}} com_x(t)}{n_{COM}} : com_x < 0$
Avg_x, Avg_y	Average value of com_x and com_y. Two features (x,y) per playthrough	$\frac{\sum_{t=1}^{n_{COM}} com_x(t)}{n_{COM}}, \frac{\sum_{t=1}^{n_{COM}} com_y(t)}{n_{COM}}$
Max_x, Max_y, Min_x, Min_y	Maximum and minimum value of com_x and com_y. Two features (x,y) per playthrough	$Max\ (com_x(t), \forall t)$, $Max\ (com_y(t), \forall t)$, $Min\ (com_x(t), \forall t)$, $Max\ (com_y(t), \forall t)$
Std_x, Std_y	Standard deviation of com_x and com_y. Two features (x,y) per playthrough	$\sqrt{\frac{\sum_{t=1}^{n_{COM}} (com_i(t) - Avg_i)^2}{n_{COM} - 1}}, i = x, y$
If_{Avg}, If_{Max}	Average $if(t)$ value and maximum for the whole playthrough. Two features per playthrough	$\frac{\sum_{t=1}^{n_{COM}} if(t)}{n_{COM}}$, $Max\ (if(t), \forall t)$
$If_{Threshold,i}$	Number of times $if(t) > i, i = [0.5,1,1.5,2]$. Normalized by the total number of samples. Four features per playthrough	$\frac{N\ (if(t) > i)}{n_{COM}}, i = 0.5,1,1.5,2$
$If_{Sum_{Avg}}$, $If_{Sum_{Max}}$	Average value and maximum of the sum of the last 25 values of $if(t)$ for the whole playthrough. Two features per playthrough	$\frac{\sum_{t=1}^{n_{COM}} if_{Sum}(t)}{n_{COM}}, if_{Sum}(t) = \sum_{i=t-24}^{t} if(t)$, $Max\ (if_{Sum}(t), \forall t)$
$If_{Sum_{Overx}}$	Number of times $If_{Sum}(t) > i, i = [0.5,1,1.5,2]$. Normalized by total playthrough time. Four features per playthrough	$\frac{N\ (if_{Sum}(t) > i)}{n_{COM}}, i = 0.5,1,1.5,2$
$Step_{Avg}$	Average time between steps, excluding the first step, defining $Step_{Time}(i)$ as the time in seconds in which step i occurred, and n_{Steps} as the total number of steps in the playthrough. One feature per playthrough	$\frac{\sum_{i=2}^{n_{Steps}} Step_{Time}(i) - Step_{Time}(i-1)}{n_{Steps}}$
$Step_{Std}$	Standard deviation of time between steps, excluding the first step. One feature per playthrough	$\sqrt{\frac{\sum_{i=2}^{n_{Steps}} \left(Step_{Time}(i) - Step_{Time}(i-1) - Step_{Avg}\right)^2}{n_{Steps} - 1}}$

Table 1: System features and calculation

In total, these 16 participants played 87 levels of PDDanceCity during this period. The median number of levels per participant was 5. Each level of PDDanceCity takes approximately two to three minutes to complete, resulting in an approximated gameplay time of 10 to 15 minutes per participant. For each level, a single training instance was obtained. The data of 6 of these levels had to be discarded due to data failure, leaving 81 training instances for classification. Due to the reduced number of participants, and to minimize the risk of overfitting based on age and sex, we attempted to classify if the player's predicted 30CST score was above or below a cutoff score of 12 points, without using these nominal data (age and sex) as features. We refer to players classified above this cutoff as fit, and those under the cutoff as not fit. This score was chosen to even out both groups, as eight participants had a 30CST score of 11 or lower. We also explore the possibility of predicting the adjusted cutoffs, which we discuss at the end of the results section. All classification tasks were performed using Weka [16].

Results

The best classification results are presented in Table 2. This decision tree used the average time between steps exclusively, with a score of 6.17 or lower indicating a participant without an increased falling risk. A comparison of different classification algorithms is presented in Figure 5. In all cases, we performed our classification using ten-fold cross-validation. Results of a feature selection analysis (information gain attribute evaluation) are included in Table 3. No features were excluded for classification.

Table 2: Best classification results

Algorithm: Logistic Model Tree, accuracy 91.358%	Correctly classified	Incorrectly classified	TP rate	FP rate	Precision	Recall	F	MCC	ROC area	PRC area
Not fit	29 (TP)	5 (FN)	0.853	0.043	0.935	0.853	0.892	0.823	0.940	0.946
Fit	45 (TN)	2 (FP)	0.957	0.147	0.900	0.957	0.928	0.823	0.940	0.930
Weighted average	74	7	0.914	0.103	0.915	0.914	0.913	0.823	0.940	0.936

Table 2: Best classification results using a Logistic Model Tree. TP = True Positive, FP = False Positive, F = F-measure, MCC = Matthews Correlation Coefficient, ROC = Receiver-Operating Characteristic Curve, PRC = Precision-Recall Curve

As a second potential scenario of analysis, we also aimed to predict the age- and sex-adjusted 30CST cutoff scores. The resulting accuracy was very high (99%) but, as discussed in the previous section, we suspect that to be due to overfitting to age and sex because of our limited sample size, as the classifier did achieve 100% accuracy using exclusively age and sex as features. If we remove these two features in this scenario, we achieve a classification accuracy of 86% predicting the age- and sex-adjusted 30CST outcome. For this reason, we believe that provided a large (and diverse) enough sample size of participants of a wide array of ages and different degrees of fitness, it should be possible to predict the age- and sex-adjusted 30CST binary result using the methods presented in this publication.

Table 3: Information gain attribute results

Feature	Information Gain (Δ Entropy)
$Step_{Avg}$	0.486
$If_{Sum_{Over0.5}}$	0.321
$If_{Sum_{Over1}}$	0.241
$If_{Threshold,0.5}$	0.178
$Step_{Std}$	0.145
If_{Avg}	0.14
$If_{Sum_{Avg}}$	0.14
If_{Max}	0.138
$Balance_{Left}$	0.118

Table 3: Information gain attribute results based on delta entropy information gain

We complemented this classification with an analysis of the effect sizes of each feature between the fit and not fit groups, measured on the basis of Hedges' g due to the low sample size and the disparity in standard deviations. We also evaluated statistical significance using a t-test. These effect sizes are presented in Table 4. Features related to the instability factor and the mean and standard deviation of the time between steps seem to contain the most information related to the 30CST. In accordance with Cohen's rule of thumb (0.2 is a small, 0.5 a medium and 0.8 a large effect size), the effect sizes of these features are large, with the differences between the fit and not fit groups being in most cases very significant ($p<0.001$) or at least significant ($p<0.05$).

Table 4: Effect size and statistical significance of features

Feature	Not fit-fit effect size (g)	Not fit-fit significance (p)	Feature	Not fit-fit effect size (g)	Not fit-fit significance (p)
$Com_{Avg_{Up},x}$	0.3168	0.1998	Avg_y	-0.0056	0.9817
$Com_{Avg_{Up},y}$	-0.4678	0.0595	Max_x	-0.3507	0.1528
$Com_{Avg_{Down,x}}$	0.2790	0.2692	**Max_y**	**-0.5279**	**0.0310**
$Com_{Avg_{Down,y}}$	-0.1171	0.6238	Min_x	0.3565	0.1472
$Com_{Avg_{Right},x}$	-0.2328	0.3404	Min_y	-0.1036	0.6630
$Com_{Avg_{Right},y}$	-0.4073	0.1028	**Std_x**	**-0.6665**	**0.0068**
$Com_{Avg_{Left},x}$	0.2661	0.2756	Std_y	-0.3789	0.1247
$Com_{Avg_{Left},y}$	-0.3234	0.1863	**If_{Avg}**	**-0.7478**	**0.0035**
$Com_{Std_{Up,x}}$	-0.0323	0.8966	**If_{Max}**	**-0.6337**	**0.0119**
$Com_{Std_{Up,y}}$	**-0.4913**	**0.0461**	**$If_{Threshold,0.5}$**	**-0.7452**	**0.0024**
$Com_{Std_{Down,x}}$	0.2234	0.3490	$If_{Threshold,1}$	-0.2411	0.2873
$Com_{Std_{Down,y}}$	0.4173	0.0860	$If_{Threshold,1.5}$	0	0
$Com_{Std_{Right,x}}$	0.0318	0.8977	$If_{Threshold,2}$	0	0
$Com_{Std_{Right,y}}$	0.0753	0.7621	**$If_{Sum_{Avg}}$**	**-0.7387**	**0.0038**
$Com_{Std_{Left,x}}$	-0.3164	0.1959	$If_{Sum_{Max}}$	-0.2107	0.3938
$Com_{Std_{Left,y}}$	-0.0237	0.9217	**$If_{Sum_{Over0.5}}$**	**-1.5261**	**<0.0001**
$Balance_{Up}$	0.1598	0.5215	**$If_{Sum_{Over1}}$**	**-0.9196**	**0.0003**
$Balance_{Down}$	0.1623	0.4988	$If_{Sum_{Over1.5}}$	-0.2206	0.3477
$Balance_{Right}$	-0.3628	0.1429	$If_{Sum_{Over2}}$	-0.2062	0.3762
$Balance_{Left}$	**0.6306**	**0.0091**	**$Step_{Avg}$**	**1.2260**	**<0.0001**
Avg_x	0.1925	0.4267	**$Step_{Std}$**	**0.8446**	**0.0020**

Table 4: Effect size and statistical significance of features. All values are presented as not fit vs. fit, meaning a negative effect size indicates the parameter has lower values in the not fit group. According to Cohen's rule, g>0.8 indicates a large effect size. p<0.05 denotes statistical significance

Discussion

Despite our limited number of participants and training instances, we obtained excellent classification results. Generally, decision trees seem to provide the best performance in the proposed classification task. Our study also presents a design limitation due to using the 30CST as a validation method. Although we decided on using the 30CST to minimize the risk of falls in study participants while conducting the test, this test is less correlated to the risk of falling than other options such as the Berg Balance Scale. A future study with a larger cohort should consider using this method instead of the 30CST to further support the hypothesis that EBB data can be used to accurately identify participants at an increased falling risk. In addition, further balance-related data from participants (Physiological Profile Assessment, functional balance, gait speed, prior falls…) should be collected as well.

Our design also presents some technical limitations. At the moment, the WBBs send the data via Bluetooth, which means they have to be manually connected for each play session. They also operate on batteries, and when these are low the data received is not reliable anymore. Additionally, the EBB frame presents a risk depending on how the EBB is placed in its surroundings: if it is not set against a wall behind it, a player may fall when taking a step backwards. We aim to address these technical limitations in a future iteration of the EBB by providing direct electrical supply to the WBBs, automating the Bluetooth synchronization process and building a complete enclosure around the EBB.

Conclusions

In spite of the aforementioned limitations, we believe our results suggest that the EBB, as an extension of the WBB, can be used to screen the elderly population for individuals with an increased risk of falling, as a basis to perform therapeutic and rehabilitation adjustments. Nevertheless, a larger dataset is required to determine the feasibility of predicting if a participant will be above or below their age- and sex-adjusted 30CST cutoff score. This could also open the possibility of predicting the result of similar tests, such as the Berg Balance Scale or the Ten-Meter Walk Test. Once the technical limitations of the EBB are addressed, and considering that participants played without supervision, a home (or, more generally, unsupervised) scenario seems feasible. In the future, we aim to extend our evaluation including features related to game performance, with the goal of performing a similar evaluation concerning cognition. This could be done, for example, on the basis of the Mini-Mental State Examination.

Declarations

Ethics approval and consent to participate

This work was submitted for consideration at the ethics committee of TU Darmstadt, case number EK09/20, approved on 17.03.2020. In accordance to the declaration of Helsinki, all participants willingly and freely took place in this evaluation, reading and signing an informed consent in which the goal of the study, their tasks, the information to be collected and the treatment of this information (pseudonymization) was presented in understandable language.

Consent for publication

Not applicable.

Availability of data and materials

Due to the nature of the data, the feature datasets of the presented classification are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Author's Contributions

HB conducted the study at the nursing home with assistance from AGA, who designed the study and its goals. Data processing was performed by AGA with help from PNM and TT. AM and SG supervised the complete study, including improving the study design and protocol and assisting with the redaction of the manuscript. All authors have contributed to writing the manuscript and have reviewed it prior to submission.

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Figure 1: PDDanceCity exergame
Figure 2: PDDanceCity scenario setup
Figure 3: EBB coordinate system
Figure 4: EBB center of mass calculation
Figure 5: Classification accuracies

Legends to figures

Figure 1: PDDanceCity exergame

Figure 2: PDDanceCity setup

Figure 3: EBB coordinate system

Figure 4: Calculation of the center of mass (top) and position of the feet (bottom) during a step forward (“a”), while standing on the center (“b”) and during a step leftwards (“c”)

Figure 5: Classification accuracies