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Assessing Dynamic Postural Control During Exergaming in Older Adults: a Probabilistic Approach

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Abstract

Digital games controlled by body movements (exergames) have been proposed as a way to improve postural control among older adults. Exergames are meant to be played at home in an unsupervised way. However, only few studies have investigated the effect of unsupervised home-exergaming on postural control. Moreover, suitable methods to dynamically assess postural control during exergaming are still scarce. Dynamic postural control (DPC) assessment could be used to provide both meaningful feedback and automatic adjustment of exergame difficulty. These features could potentially foster unsupervised exergaming at home and improve the effectiveness of exergames as tools to improve balance control. The main aim of this study is to investigate the effect of six weeks of unsupervised home-exergaming on DPC as assessed by a recently developed probabilistic model. High probability values suggest ‘deteriorated’ postural control, whereas low probability values suggest ‘good’ postural control. In a pilot study, ten healthy older adults (average 77.9, SD 7.2 years) played an ice-skating exergame at home half an hour per day, three times a week during six weeks. The intervention effect on DPC was assessed using exergaming trials recorded by Kinect at baseline and every other week. Visualization of the results suggests that the probabilistic model is suitable for real-time DPC assessment. Moreover, linear mixed model analysis and parametric bootstrapping suggest a significant intervention effect on DPC. In conclusion, these results suggest that unsupervised exergaming for improving DPC among older adults is indeed feasible and that probabilistic models could be a new approach to assess DPC.

Keywords: unsupervised home exergaming, assessment of dynamic postural control, probabilistic models, curvature and speed of body movements.

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1. Introduction

Maintaining good postural control in the population older than 60 years is an essential skill to prevent falls. Falls can cause severe injuries, disability, and in the worst case death [1]. In addition, with advancing

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age the incidence of falls increases. Exercise can improve postural control and thereby reduce the risk of falls among the older population [2]. Exergames, a combination of exercise and digital games (also called active video games), have been proposed as a way to improve postural control [3]. Although there is a considerable number of exergames available [4], the number of unsupervised intervention studies involving older adults is still limited [5]. Moreover, suitable methods to assess dynamic postural control (DPC) during exergaming are still scarce. Hence, further research is needed to investigate the effect of unsupervised exergaming at home on DPC.

DPC assessment could be used to provide both meaningful online feedback about postural control skill and automatic adjustment of exergame difficulty. In addition to gaming scores, online feedback based on DPC assessment could increase players' motivation preventing abandonment. Dynamic difficulty adjustment could be used to prevent overexertion providing appropriate game pacing [6]. These valuable features could potentially foster unsupervised exergaming at home and improve the effectiveness of exergames as tools to improve balance control. Indeed, one of the promises of exergames is the ability to train at home at any time, independently of the weather conditions and avoiding also the effort and cost of traveling.

A promising ice-skating exergame controlled by body movements tracked by Microsoft Kinect 1 has been developed to improve postural control among older people [7]. This exergame has been designed to train lateral body movements, as the deterioration of this kind of motion has been associated with fall risk [8].

Recently we proposed the assessment of DPC using a generalized linear model (GLM) [9], which is a probabilistic model. The assessment is based on curvature –as a measure of smoothness– and speed of body movement trajectories [10]. As younger adults generally have better postural control than older adults [11], estimating the degree to which human body movements are similar to those of older adults can be a way to assess postural control. The GLM developed in [10] expresses this degree as a probability value (between 0 and 1). High probability values suggest a 'deteriorated' postural control ability similar to those of older adults, whereas low probability values suggest 'good' postural control similar to those of younger adults. The mathematical definition of the GLM is based on the assumption that the outcome variable follows a Bernoulli distribution that can attain two values: 0, meaning that the measures (curvature and speed) were collected from a younger participant (60 years old or younger), and 1, meaning that the measures were collected from a participant older than 60 years. This GLM was trained using data collected from 20 older and 20 younger participants. These participants executed ten trials of one minute ice-skating game-play. The predictive accuracy of the GLM was assessed using the Watanabe-Akaike information criterion (WAIC)[12] and its dynamic performance was tested using five-fold cross-validation [13]. The GLM achieved more than 90% accuracy in cross-validation, showing promise for DPC assessment during exergaming.

In the present study we investigate the effect of six weeks of unsupervised home-exergaming on DPC as assessed by the probabilistic model where high values suggest a 'deteriorated' DPC ability. During the intervention, we expect improvement on DPC ability to be reflected in decreasing probability values.

2. Methods

The effects of six weeks of home-exergaming intervention on quiet-standing balance control, as assessed by measures derived from the center of pressure trajectories, have been reported previously in Van Diest *et al.* [14]. Here, we report the intervention effect on DPC using body movement trajectories collected by Kinect and assessed by a recently developed probabilistic model.

2.1. Participants

Ten healthy older adults (five males; mean age 79.9 years old, SD 7.2) participated in the pilot intervention program. The participants were able to walk for at least 15 minutes without aid (self-reported). None of the participants had exergaming experience. Participants with orthopedic or cognitive impairments affecting their postural control ability were not considered for this study. The study was approved by the Medical Ethical Committee, University Medical Center Groningen, and was conducted in accordance with the declaration of Helsinki. All participants provided written informed consent before the intervention.

2.2. Procedure and instrumentation

The participants played the ice-skating exergame for about 30 minutes a day, three times a week, during six weeks. The participants had at least one resting day in between each 30 minutes of exergaming. The exergame was played in two modes, *coordination* and *endurance*. In the former mode, the participants had to complete an ice-skating track as fast as possible without ‘virtual’ falls. A virtual fall is the result of hitting obstacles or falling in an ice hole in the virtual environment. The lengths of the tracks were 300, 600, and 1500 meters, respectively, and were self-selected by the participants. In the latter mode, the participants had to “skate” as far as possible, on a straight ice-skating track without obstacles or holes, within a self-selected period of 1, 2, or 5 minutes.

2.3. Data

To assess DPC, the participants performed 10 exergaming trials four times, at baseline and after 2, 4 and 6 weeks of exergaming. The length of the trials was fixed at 300 m. Of the 10 trials, five trials were in coordination mode and five in endurance mode. In the coordination mode the tracks included 15 obstacles. On average the trials lasted 75.6 seconds (SD 22.9 seconds). The trajectories of whole body movements were recorded by Microsoft Kinect 1 during game-play. In total 400 trials were recorded (10 participants, 10 trials per participant recorded 4 times during the intervention period).

2.4. Data preprocessing

The Kinect data were resampled at 30Hz to avoid sample frequency deviations. The first and last 5 seconds were removed. The first 80 seconds of trial number 3, in coordination mode from participant 9,

were removed because of erroneous Kinect recordings. As a result 71 seconds (of this trial) remained for analysis.

2.5. Dynamic postural control assessment

We continuously assessed DPC along the recorded trials using the GLM (model m_{11}) parameters estimated in [10]. This GLM estimates the probability $\mathbb{P}$ that the body movements recorded by Kinect belong to a participant older than 60 years. $\mathbb{P}$ is estimated as a function of local curvature and instantaneous speed derived from mid-shoulder and right-knee body parts. The local curvature of the trajectory movements was approximated by taking the inverse of the radius of a circle fitted to each three consecutive data points [15]. Curvature can be understood as the degree to which the trajectory deviates from being straight. Thus, straight trajectories have zero curvature, parts of the trajectory where large circles can be fitted have low curvature and parts of the trajectory where small circles can be fitted have high curvature. From a postural control perspective, low curvature corresponds to the ability of participants to perform smooth movements. Curvature and speed signals were smoothed using one-second running means. For each week (baseline, 2, 4, and 6), the mean $\bar{\mathbb{P}}$ was estimated for each participant $j = 1 \dots 10$ and game-play mode k (coordination and endurance).

2.6. Data visualization

We used visualization techniques as a way to gain qualitative insight into the structure of the data and to identify patterns that could be used for further data analysis. Heat maps were used to simultaneously visualize the performance of all participants across time, representing trials by vertical lines and performance by color. Parallel coordinates [16] and box plots were used to visualize the distribution of performance values ($\mathbb{P}$) for each week of assessment.

2.7. Statistical analysis

Hierarchical linear mixed models (LMM) [17] were used to investigate the effect of six weeks of exergaming on DPC. One of the best ways to deal with data that represents percentages or probabilities is to use the *logit* transform [18]. This transformation allows us to meet the requirement of normality among the LMM residuals. At the first level (i) of the hierarchy we used mean values $\bar{\mathbb{P}}'$ (*logit* transformed), and the second level is represented by the participants (j). Thus, the following LMMs were defined:

$$\bar{\mathbb{P}}'_{ij} = \gamma_{00} + R_{ij} \quad (1)$$

$$\bar{\mathbb{P}}'_{ij} = \gamma_{00} + \gamma_{10} \cdot week + R_{ij} \quad (2)$$

$$\bar{\mathbb{P}}'_{ij} = (\gamma_{00} + U_{0j}) + \gamma_{10} \cdot week + R_{ij} \quad (3)$$

$$\bar{\mathbb{P}}'_{ij} = (\gamma_{00} + U_{0j}) + (\gamma_{10} + U_{1j}) \cdot week + R_{ij} \quad (4)$$

Model	DF	AIC	BIC	LogLik	pValue
(1)	2	458.63	463.39	-227.31	
(2)	3	416.89	424.03	-205.44	3.7514e-11
(3)	4	412.45	421.97	-202.22	0.011154
(4)	6	414.93	429.22	-201.46	0.46828

Table 1: Model comparison results for each two consecutive models. DF - degrees of freedom, AIC - Akaike information criterion. BIC - Bayesian information criterion, LogLik - Maximized log likelihood, pValue - p-value for the likelihood ratio test (as a result of the comparison of each two consecutive models).

The parameter estimated for model 1 is the global mean (γ_{00}) and is used only as reference. For all models R_{ij} are the residuals from the fits. The parameters estimated for model 2 are the global intercept (γ_{00}) and the global slope (γ_{10}), *week* is the predictor of the model and represents the time of exergaming, that is, 0, 2, 4, and 6 weeks. For model 3, in addition to the global intercept and slope, intercept deviations (random intercepts) per participant (U_{0j}) are also estimated. Model 4 adds the slope deviations per participant (U_{1j}), or random slopes.

To select the model that best fit the data, the likelihood ratio test (LRT) was used to compare the models [19], while the Akaike information criterion (AIC) [20] and Bayesian information criterion [21] were also estimated. However, the LRT performance can be poor and misleading when testing the presence of fixed effects (in our case, the effect of exergaming on DPC) for small and moderate sample sizes [22]. To address this limitation, we used a parametric bootstrapping approach. To explore the importance of fixed effects, the model that contains the effects are compared with a model that excludes them [19]. Thus, the best model (Eq. 3, see Table 1) was re-fitted without the predictor *week* by using the following equation,

$$\bar{\mathbb{P}}'_{ij} = (\gamma_{00} + U_{0j}) + R_{ij}, \quad (5)$$

and both models were compared using parametric bootstrapping performing 1000 simulations.

3. Results

The visualization in Figure 1 shows the DPC performance $\mathbb{P}$ of the participants across trials and weeks. Color represents $\mathbb{P}$ -values, orange colors suggest that DPC is similar to that of older people, while green colors suggest that DPC is similar to that of younger people. Vertical lines illustrate the performance of participants within a trial, and the horizontal axis shows their performance across weeks. At baseline (week 0) all participants scored high $\mathbb{P}$ -values, illustrated by the mostly orange colors. In general, the transition from “orange” to “green” across weeks suggests that all participants improved DPC in both game-play modes (coordination and endurance). This improvement can also be derived from the length of the trials, as most of the participants finished the ice-skating tracks faster during the last two weeks of the intervention

Model	DF	AIC	BIC	LogLik	pValue
(5)	2	460.63	467.77	-227.31	
(3)	4	412.45	421.97	-202.22	0.000999

Table 2: Results of the parametric bootstrapping (1000 simulations) to test the intervention effect on dynamic postural control. DF - degrees of freedom, AIC - Akaike information criterion. BIC - Bayesian information criterion, LogLik - Maximized log likelihood, pValue - p-value (result of the comparison between the two models).

than during the first two weeks. It can also be seen, however, that most of the participants improved more at endurance game-play mode than at coordination game-play mode, with the exception of participants 5 and 10 who improved equally across modes. In coordination mode, to avoid obstacles the participants had to decrease speed and increase curvature of the trajectories which is generally reflected in high $\mathbb{P}$ -values (orange). Also, consistent with [14], it can be noticed that each participant improved at his/her own pace. For example, participants 1 and 5 show more improvement at the second week in endurance mode than, e.g., participants 4 and 7. This is also reflected in the last assessment (week 6) as compared to baseline; participants 1, 5, and 10 improved more at DPC than, e.g., participants 4, 7, and 9.

Figure 2 shows the distribution of DPC performance $\mathbb{P}$ and logit transformed $\mathbb{P}'$ as box plots, per week and game-play mode. Similar to Figure 1, the box plots allow to observe that $\mathbb{P}$ and $\mathbb{P}'$ -values decrease over time, that is, performance increases over time, for both game-play modes. Also, more clear differences can be observed between baseline and week 6 in endurance mode than in coordination mode. In particular, points, polylines, and dashed lines show the DPC performance per participant across the intervention period. In general, the negative slopes of the dashed lines (linear fits on the means) suggest that all participants improved at DPC during exergaming.

The LRT results in Table 1 show that model 2, without random effects (i.e., the model with fixed intercept and slope, Eq. 2) fits the data significantly better than the empty model 1 ($p < 0.0001$). Model 3 including only random intercepts (Eq. 3) is significantly better ($p < 0.05$) than model 2. The most complex model 4 (Eq. 4), which includes both random intercepts and random slopes, is not significantly better than model 3. Hence, the model that best fits the data is model 3 (Eq. 3) with random intercepts only. As random effects influence the variance of DPC, these results suggest significant intercept variation among participants, but no significant slope variation. Consistent with the line fits on $\mathbb{P}'$ -values (Figure 2) these results suggest that all participants improved at a similar rate (in logit scale).

Parametric bootstrapping indicates that the effect of six weeks of exergaming on dynamic postural control is highly significant ($p < 0.001$, Table 2). The smaller values of AIC and BIC also support this result.

Figure 1: Performance P of the participants (ppt) during dynamic postural control assessment. Each vertical line represents one exergaming trial; in total 400 trials are visualized. Each box represents the trials of a participant in a particular game-play mode, endurance or coordination (upper and lower boxes per participant, respectively). Orange colors suggests that balance performance is similar to that of older people, while green colors suggest that performance is similar to that of younger people. White vertical lines have been added to separate trials between weeks. White parts within trials indicate missing data. For improved visualization the trials have only been plotted for the first 65 seconds.

Figure 2: Box plots showing the distribution of dynamic postural control values during exergaming: non transformed IP and logit transformed IP' in the two game-play modes *endurance* and *coordination*. Colored points and polylines represent participants (ppt), points in the box plots are the means per participant, and dashed lines represent piece-wise linear fits on the means. The black shaded bars at the extremes of some boxplot whiskers represent outliers (values smaller or larger than the median ± 1.5 times the interquartile range).

140 4. Discussion

Our main goal was to investigate the effect of six weeks of unsupervised ice-skating exergaming on dynamic postural control as assessed by a metric recently developed for real-time balance assessment. Our results show that participants improved at DPC after six weeks of exergaming suggesting a positive effect of the intervention.

145 First, we assessed dynamic postural control at baseline and every other week during the intervention using a probabilistic model (GLM) that predicts how likely the body movements are similar to those of people older than 60 years. This metric was estimated as a function of instantaneous speed and local curvature of the movement trajectories. Second, we used visualization techniques to qualitatively show how the participants improved over time. Finally, linear mixed models and parametric bootstrapping simulations
150 confirmed a significant intervention effect of exergaming on DPC.

In a previous study [10], we estimated the GLM parameters to characterize human movements recorded during exergaming as the probability that the movements belong to people older than 60 years. Here we used these GLM parameters to assess DPC during a long unsupervised home exergaming intervention. At baseline all participants exhibited ‘declined’ DPC as people older than 60 years, illustrated in Figures 1
155 and 2. As time of exergaming training increased, the participants showed improvement at DPC, which was reflected, as we expected, in lower probability values. This provided additional evidence of 1) the usefulness of our GLM method for DPC assessment, and 2) the effectiveness of exergames as tools to improve postural control, which is consistent with the results of other unsupervised home exergaming studies [5, 23].

The assessment of static stand-still tasks for this intervention program has been reported in a previous
160 study. In that study only static balance was assessed and significant effects were found on several posture measures but not on all, and not for all conditions [14]. Our study complements the results in [14] by further assessing performance of the participants at DPC. Here, we found a significant intervention effect on DPC during exergaming. These results suggest that dynamic measures are important to highlight the effectiveness of exergames as tools that can improve dynamic postural control among older adults.

165 One of the limitations of the present study is that the number of participants is small; to moderate this, we applied parametric bootstrapping as an accepted method to check the stability of the results. Also, the present exergaming study was a single-subject design, meaning that no control group was incorporated during the intervention. Further research involving a control group with no exercise and a conventional home exercise program with minimal supervision could provide additional evidence of the effectiveness
170 of exergames to improve (dynamic) postural control. Further studies are also necessary to translate the probability scores into clinical outcome measures that can be more easily interpreted by clinical users.

A promising application of our DPC assessment method is the possibility to offer direct online feedback during exergaming because the assessment can be estimated in real-time, as curvature and speed can be

measured instantaneously. Direct feedback about performance is important for therapy adherence [24].
 175 Moreover, the presented method is robust to outliers, as sample values extremely far away from the mean are mapped to a number between 0 and 1. Finally, our metric provides a natural and meaningful interpretation of the results, as values close to 0 suggest performance similar to younger adults and values close to 1 suggest performance similar to older adults.

A desirable feature of exergames is dynamic difficulty adjustment (DDA) [25], that is the automatic
 180 adjustment of difficulty level. Such a feature could be used to tailor the level of exercises to the individual skills during game-play. This will ensure optimal challenge level and skill learning, avoiding boredom or frustration and feelings of failure [26].

In general, our method based on probabilistic models is highly versatile because 1) it does not depend on a particular kind of tracking technology, allowing the use of different kinds of devices such as inertial
 185 sensors, force plates, infrared and visible cameras; 2) probabilistic models could also be used to classify or characterize movement patterns of different populations or in other areas such as sports; and 3) probability values could be estimated not only as a function of curvature and speed but also as a function of various kinds of other motion features such as trajectory invariants [27], acceleration, and turbulence intensity [28]. Once the parameters of a model have been estimated, they could be used to assess movement disorders,
 190 movement performance in sports or rehabilitation, and specific interventions aimed at optimizing movement performance.

In conclusion, we have presented additional evidence of the effectiveness of unsupervised home-exergaming as a way to improve dynamic postural control. Furthermore, we have shown that our approach, employing a probabilistic model, is promising for DPC assessment during exergaming. The next step in our research is to
 195 investigate the effect of providing instantaneous feedback during ice-skating exergaming based on real-time DPC assessment as described in this study.

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Conflict of interest

The authors declare that they have no competing interests.

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Highlights

- Unsupervised home exergaming improves dynamic postural control (DPC) in older adults
- Probabilistic models can be a novel approach to assess DPC in real time
- Real time DPC assessment could be used to provide meaningful feedback in exergames
- Real time DPC assessment could be used for dynamic difficulty adjustment in exergames