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2012 Physiol. Meas. 33 1855

(http://iopscience.iop.org/0967-3334/33/11/1855)

IOP Publishing PHYSIOLOGICAL MEASUREMENT

Physiol. Meas. **33** (2012) 1855–1867 doi:10.1088/0967-3334/33/11/1855

Validation of seat-off and seat-on in repeated sit-to-stand movements using a single-body-fixed sensor

R C van Lummel[1], E Ainsworth[1], J M Hausdorff[2], U Lindemann[3], P J Beek[4] and J H van Dieën[4]

[1] McRoberts Raamweg 43, 2596 HN, The Hague, The Netherlands
[2] Department of Physical Therapy, Sackler Faculty of Medicine, Tel-Aviv University and Department of Neurology, Tel Aviv Sourasky Medical Center, Israel
[3] Department of Clinical Gerontology, Robert-Bosch Hospital, Auerbachstr. 110, D-70376, Stuttgart, Germany
[4] Faculty of Human Movement Sciences, Research Institute MOVE, VU University Amsterdam, Amsterdam, The Netherlands

E-mail: rcvanlummel@mcroberts.nl

Received 30 March 2012, accepted for publication 18 July 2012
Published 31 October 2012
Online at stacks.iop.org/PM/33/1855

Abstract

The identification of chair rise phases is a prerequisite for quantifying sit-to-stand movements. The aim of this study is to validate seat-off and seat-on detection using a single-body-fixed sensor against detection based on chair switches. A single sensor system with three accelerometers and three gyroscopes was fixed around the waist. Synchronized on–off switches were placed under the chair. Thirteen older adults were recruited from a residential care home and fifteen young adults were recruited among college students. Subjects were asked to complete two sets of five trials each. Six features of the trunk movement during seat-off and seat-on were calculated automatically, and a model was developed to predict the moment of seat-off and seat-on transitions. The predictions were validated with leave-one-out cross-validation. Feature extraction failed in two trials (0.7%). For the optimal combination of seat-off predictors, cross-validation yielded a mean error of 0 ms and a mean absolute error of 51 ms. For the best seat-on predictor, cross-validation yielded a mean error of –3 ms and a mean absolute error of 127 ms. The results of this study demonstrate that seat-off and seat-on in repeated sit-to-stand movements can be detected semi-automatically in young and older adults using a one-body-fixed sensor system with an accuracy of 51 and 127 ms, respectively. The use of the ambulatory instrumentation is feasible for non-technically trained personnel.

This is an important step in the development of an automated method for the quantification of sit-to-stand movements in clinical practice.

Keywords: seat-off, seat-on, sit-to-stand, assessment, accelerometer, gyroscope

(Some figures may appear in colour only in the online journal)

1. Introduction

Sit-to-stand (STS) tasks are frequently used as a test of motor function in clinical populations (Guralnik *et al* 2011, Penninx *et al* 2000, Volpato *et al* 2008, Guralnik *et al* 1994, Rolland *et al* 2006). In current clinical practice, the total time to perform this task is used as the outcome variable, while several studies suggest that valuable information may be obtained by assessing the duration of the different phases of the task (Najafi *et al* 2002, Ikeda *et al* 1991, Lord *et al* 2002, Janssen *et al* 2002). The identification of chair rise events is a prerequisite for such an analysis. STS events of particular interest are seat-off and seat-on because these mark the transitions to and from an intrinsically stable three-point support (i.e. sitting) and a dynamically stable two-point support (i.e. standing) (Riley *et al* 1991). Leaving the chair seat is a critical factor for a successful STS. It yields higher peak hip contact pressures and requires greater moment and range of motion at the knee than gait or stair climbing (Hughes *et al* 1996). The seat-off has been used to separate STS sub-phases (Schenkman *et al* 1990, Riley *et al* 1991, Lindemann *et al* 2007) and to synchronize different strategies of STS (Doorenbosch *et al* 1994, Hirschfeld *et al* 1999).

The gold standard for the identification of the moment of seat-on and seat-off is to measure the vertical loading on the chair using seat switches (Kralj *et al* 1990), a force platform under the chair (Pai and Rogers 1990, Alexander *et al* 1991, Hirschfeld *et al* 1999, Zijlstra *et al* 2010) or load-cells (Papa and Cappozzo 1999). If an instrumented chair is not available, foot–floor reaction forces are used to estimate the moment of seat-off. Several features of the ground reaction force signals have been used to predict seat-off in previous studies: (1) time of peak of horizontal ground force (Kralj *et al* 1990); (2) time of peak of vertical ground force (Riley *et al* 1990); (3) time of 100% body weight vertical ground force (McGibbon *et al* 2004).

Since the early 1990s, body-fixed sensors (BFS) have increasingly been used to measure kinematic and kinetic parameters (Veltink and van Lummel 1994). BFS have several advantages. Miniaturizing electronics has made it possible to develop small and light devices including sensors to capture accelerations and angular velocities in three orthogonal planes. These devices are unobtrusive and can be positioned anywhere on the body with low patient awareness. Advances in ergonomic design and fixation methods have improved patient acceptance (Regueiro *et al* 2011) and enabled some patients to wear the BFS system for several weeks. This makes it possible to move from the lab to daily life settings.

Previous studies using BFS during the analysis of STS movements have demonstrated the ability to: (1) identify the beginning and end of STS transitions, with one gyroscope fixed to the chest (Najafi *et al* 2002) and with accelerometers and gyroscopes fixed to the trunk (Giansanti and Maccioni 2006); (2) decompose accelerometric signals on the trunk and thigh (Janssen *et al* 2005); (3) combine two accelerometers and one gyroscope to improve the accuracy to measure trunk and thigh angles (Boonstra *et al* 2006); (4) reconstruct the trunk trajectory (Giansanti *et al* 2007); (5) analyze the peak power (Zijlstra *et al* 2010), (6) discriminate between healthy and frail elderly (Ganea *et al* 2011) and (7) fully automated analysis of instrumented repeated STS movements (van Lummel *et al* 2011).

The objectives of this study were: (1) to develop an automated approach for quantifying the seat-off and seat-on during STS using a single sensor located at the waist and (2) to determine the validity of this approach in young and older adults, using switches under the chair as reference.

2. Methods

2.1. Subjects

In this cross-sectional study, 15 older adults (OA) were recruited from a residential care home (age: 85.3 ± 6.4 years; height: 168.4 ± 9.3 cm; weight: 74.0 ± 11.0 kg; $M \pm SD$); they had to be able to perform at least five repeated STS movements. In addition, 15 young adults (YA) were recruited among college students (age: 20.7 ± 1.4 years; height: 183.2 ± 8.7 cm; weight: 72.9 ± 9.2 kg). The young subjects had no history of neuromuscular or musculoskeletal disorders. The protocol was approved by the ethics committee of the Faculty of Human Movement Sciences of VU University Amsterdam and all participants signed informed consent.

2.2. Equipment

A BFS system (DynaPort® Hybrid, McRoberts, The Hague, The Netherlands) was inserted in an elastic belt and positioned on the lower back at the height of the second lumbar vertebra, which is close to the body's center of mass (CoM) in the standing position. The small and light measurement system ($87 \times 45 \times 14$ mm, 74 g) contains three pre-calibrated seismic accelerometers (STM: sensor range $\pm$ 2 g, resolution 1 mg) and three pre-calibrated gyroscopes (EPSON: range $\pm$ 100 $^\circ$ s^{-1}, resolution 0.0069 $^\circ$ /s^{-1}) and has a sampling rate of 100 samples/s. The accelerometer signals have been shown to be highly reproducible (van Hees *et al* 2009). Raw data were stored on a Micro-SD card. The device can connect with a computer from a distance of up to 100 m via Bluetooth. The supporting acquisition software can start and stop the sensor system and send event markers to store analysis intervals with the data. Sensor data and chair switch data are shown in figure 1.

Four on/off switches were connected to a second DynaPort device and positioned under the corners of a plywood sheet placed underneath the chair. The adjustable thresholds were set at 98.1 N. The two DynaPort devices were synchronized using a special cable set. The sensors were connected with the cables in standby mode and started with a button. After the start of the measurement, the cables were removed.

2.3. Procedures

As illustrated in figure 2, subjects were asked to perform two sets of five STS cycles at a self-selected speed. A STS cycle is comprised of standing up (a–c), standing including stabilizing (d-e), sitting down (f-g) and sitting (h). Five STS cycles contain five periods of standing up, standing and sitting down and four sitting periods. A standard chair without arm rests (height 42 cm) was used. All trials were videotaped from the side to enable post-hoc visual inspection of successful and failed attempts. Subjects were free to swing their arms but were instructed to avoid pushing off from the chair with their hands because this meant the switches under the chair remained on and a seat-off could not be detected. If necessary, subjects were allowed to push off from their own legs.

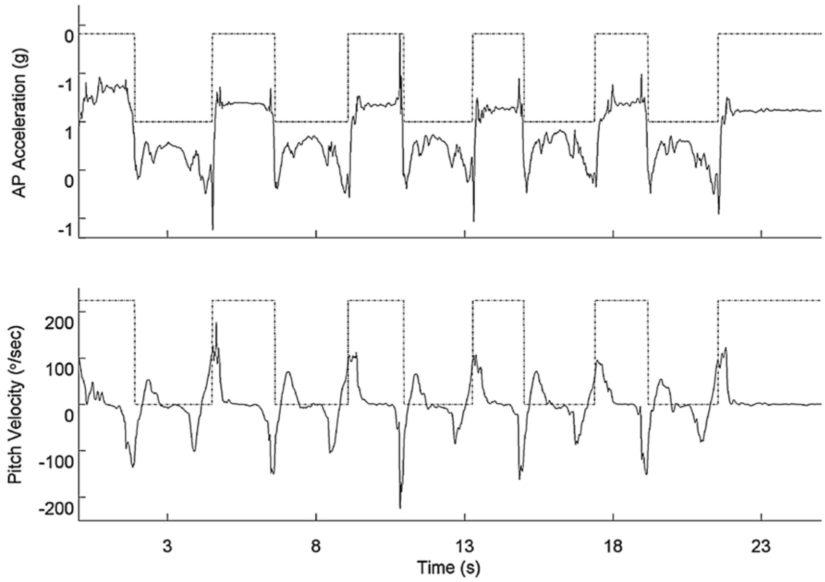

Figure 1. Example of signals of five repeated STS movements of a young adult. In the top panel the AP acceleration (g) and in the bottom panel the pitch velocity ($^\circ$ s^{-1}) of five repeated sit-to-stand-to sit trials are shown. Sensor data (solid line) and chair switch data (dashed line) were recorded in synchrony.

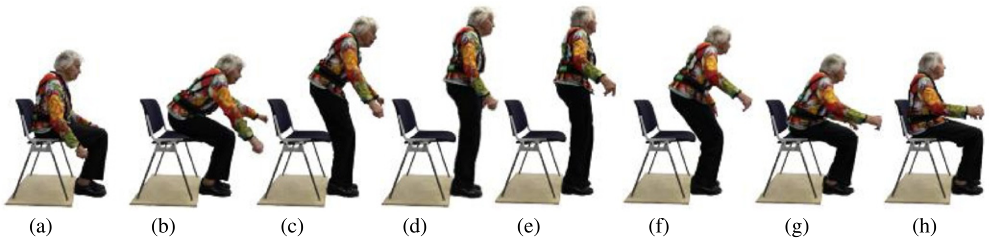

Figure 2. A STS cycle is comprised of standing up ((a)–(c)), standing including stabilizing ((d)–(e)), sitting down ((f)–(g)) and sitting (h).

2.4. Data analysis

Seat-off was detected when the chair switches underneath the two back corners of plywood were off. Seat-on was detected when three of four switches were on. Dedicated software was developed in Matlab (Mathworks, Natick MA, USA) to detect seat-off, seat-on, and to analyze trunk movements using the accelerations and angular velocities. The acceleration and the angular velocity in the sagittal plane were used to calculate the trunk pitch angle (Williamson and Andrews 2001). The effect of the angular displacement was removed from the raw accelerations using the following equations:

$$a_{\text{angle\_V}} = \sin\left(05\,\pi - \frac{\varphi}{180\,\pi}\right) \quad (1)$$

$$a_{\text{true\_V}} = a_{\text{measured\_V}} - a_{\text{angle\_V}} \quad (2)$$

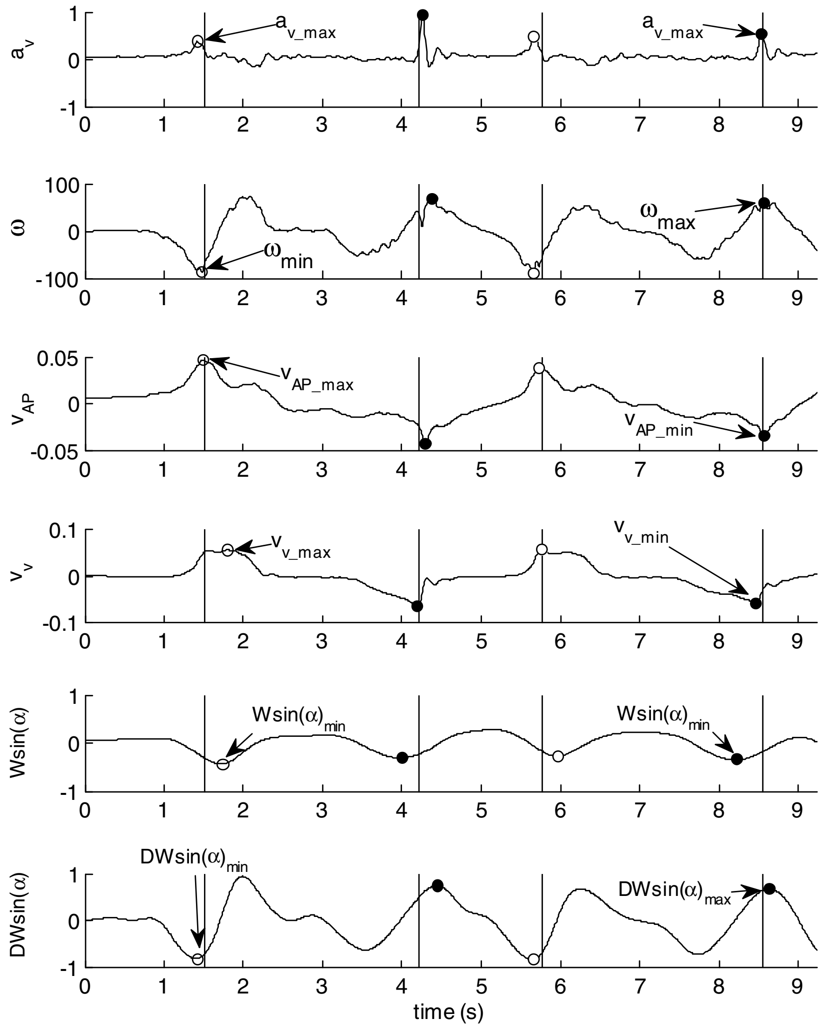

Figure 3. Example of the signals used for feature extraction of two STS repetitions from one older adult. The open circles (○) represent the estimation of the seat-off and the filled circles (•) the estimation of the seat-on. Vertical lines represent the seat-off (first and third) and seat-on (second and fourth) as detected by the chair switches.

$$a_{\text{angle\_AP}} = \text{COS}\left(05\ \pi - \frac{\varphi}{180\ \pi}\right) \tag{3}$$

$$a_{\text{true\_AP}} = a_{\text{measured\_A}\quad\text{P}} - a_{\text{angle\_AP}}, \tag{4}$$

where φ is the angle of the accelerometer with respect to the vertical.

Next, $a_{\text{true\_V}}$ and $a_{\text{true\_AP}}$ were integrated to derive vertical and anterior–posterior (AP) velocities. Additionally, a discrete wavelet transformation was performed on the sine of the trunk angle (Najafi *et al* 2002). Finally, the derivative of this signal was calculated to estimate the angular velocities.

On these signals, peak detection was performed to derive the following features as predictors of seat-off and seat-on, respectively (see figure 3)

(1) Maximum trunk vertical acceleration, a_{V_max} for both seat-on and seat-off.
(2) Minimum and maximum trunk angular velocity, ω_{min} and $\omega_{max.}$
(3) Maximum and minimum AP trunk velocity, v_{AP_max} and $v_{AP\_min.}$
(4) Maximum and minimum vertical trunk velocity, v_{V_max} and $v_{V\_min.}$
(5) Minimum of the wavelet transformed sine of the trunk angle, $\mathrm{Wsin}(\alpha)_{min}$ for both seat-on and seat-off.
(6) Minimum and maximum of the derivative of $\mathrm{Wsin}(\alpha)$, $\mathrm{DWsin}(\alpha)_{min}$ and $\mathrm{DWsin}(\alpha)_{max.}$

Each predictor had an offset relative to the reference values obtained from the chair switch signals (see figure 3). The average offset (over all trials recorded) was subtracted from the predictor variable to obtain an estimate of the seat-off or seat-on event. To increase the precision and robustness of the estimation, a combined estimate was made based on the weighted average of the individual estimates. The weight for each predictor in the model was based on the variability of the estimates obtained with the single predictors as described by equations (5) and (6):

$$w_i = \frac{1}{\mathrm{SD}_i} \tag{5}$$

$$\mathrm{weight}_i = \frac{w_i}{\Sigma_w}, \tag{6}$$

where SD is a vector containing the standard deviations of the estimates based on single predictors. Note that the larger the standard deviation, that is, the larger the uncertainty for that estimate, the lower the weight. Two models were created, one with all predictor variables combined (combined all) and one with the two best single predictors (combined optimal), i.e. the predictors that yielded the offset with the lowest mean and standard deviation. For both models, all the data of both young and older adults were used.

2.5. Statistical analysis

We determined mean differences between the estimated and reference event times. The mean difference was subtracted from the estimated event times and the standard deviation of the resulting estimates was determined as an indicator of precision.

Cross-validation, sometimes called rotation estimation, was used for assessing how the results of the analyses generalize to an independent data set. This method is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice (Kohavi 1995). Cross-validation can be done in several ways. Leave-one-out (Stone 1974 and Geisser 1975) is one option and it is more efficient than creating a hold-out set. Therefore, the predictions were validated with leave-one-out cross-validation. This involves using a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data.

3. Results

From the 15 YA and 13 OA who did 2 sets of 5 trials, 253 trials (90.4%) were analyzed successfully; feature extraction failed in only two trials (0.7%). Two OA were not able to stand up and were excluded. Eighteen trials were removed due to chair sensor problems (YA, 10 and OA, 8). A chair sensor problem means that the seat-off or the seat- on was not correctly detected, because the sensor-ground contact failed, or the sensor was switched on due to standing on the plywood, or the subject pushed off from the chair with the hands. Seven YA

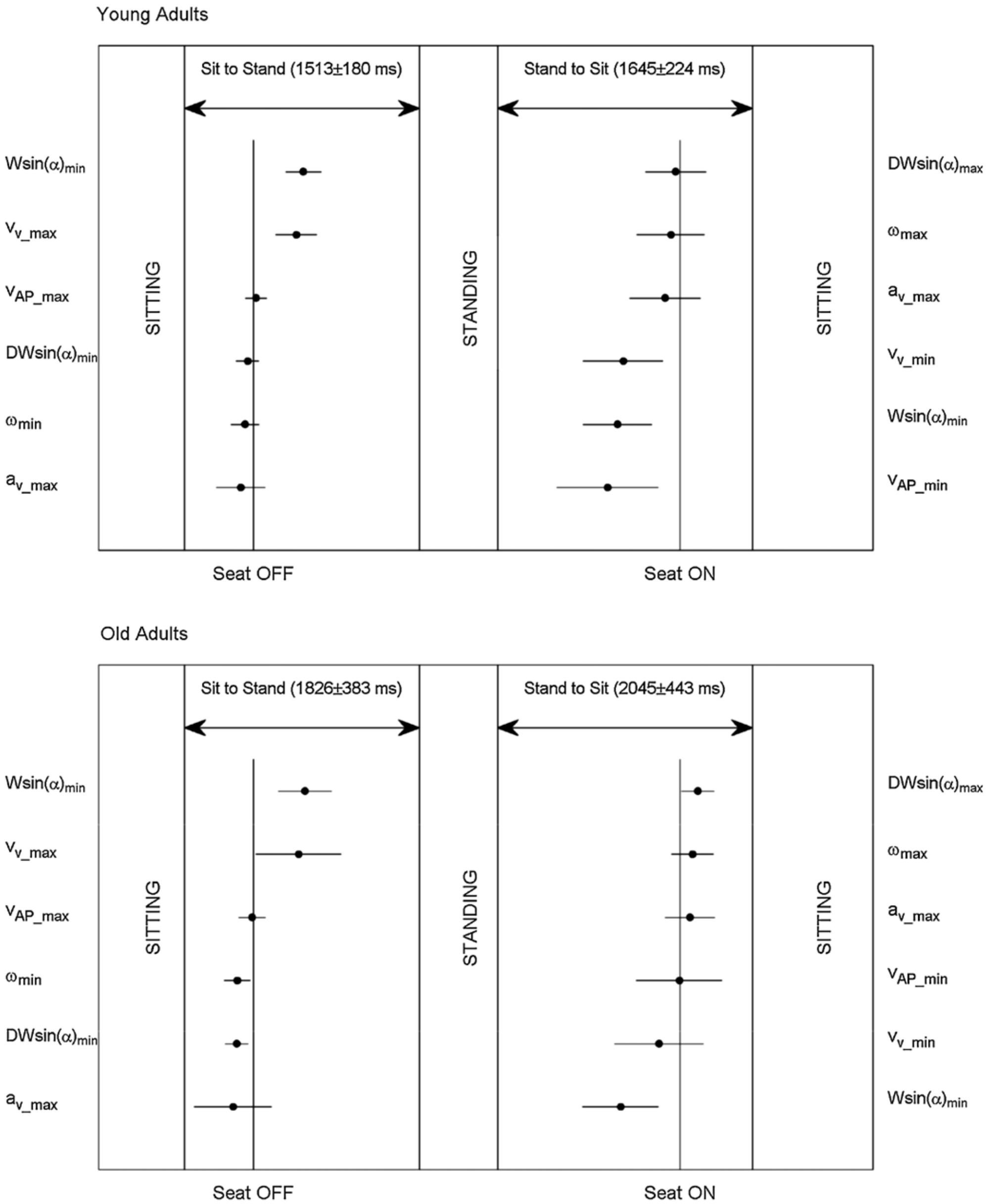

Figure 4. Offset (•) and SD (—) of the timing of each of the predictors relative to seat-off and seat-on. The results for the young adults (133 trials) are shown in the upper panel and those for the older adults (120 trials) in the lower panel. The continuous vertical lines represent the separation between the phases of the STS cycle, the shorter vertical lines represent the moments of seat-off and seat-on.

performed four instead of five trials. Two trials of OA were removed due to failed feature extraction.

Figure 3 presents a typical example of the signals from which features were extracted as predictor variables. The mean offsets relative to seat-off and seat-on and the concomitant standard deviations for the six predictors are presented in figure 4. The vertical acceleration

Table 1. Mean (SD) values of the error absolute error of the seat-off estimates based on single predictors and the two models combining several predictors (ms).

	DWsin $(\alpha)_{\min}$	Wsin $(\alpha)_{\min}$	$\omega_{\min}$	$v_{\mathrm{AP\_max}}$	$v_{\mathrm{V\_max}}$	Combined all	Combined optimal
Mean error (ms)	0 (69)	0 (122)	0 (73)	0 (69)	0 (186)	0 (74)	0 (66)
Mean abs error (ms)	51 (50)	94 (77)	63 (47)	56 (40)	161 (109)	58 (45)	49 (44)

Table 2. Mean (SD) values of the error and absolute error of the seat-off estimates based on single predictors and the model combining the two best predictors in the cross-validation (ms).

	DWsin$(\alpha)_{\min}$	$v_{\mathrm{AP\_max}}$	Combined optimal
Mean error (ms)	1 (72)	0 (71)	0 (68)
Mean abs error (ms)	52 (52)	58 (42)	51 (46)

($a_{\mathrm{V\_max}}$) was found to be imprecise because often there were no clearly detectable peaks in the signal. Therefore, $a_{\mathrm{V\_max}}$ was not used further in the analysis.

In general, the variability of the timing of the predictors relative to seat-off was much lower in the YA than in the OA and predictions of the seat-off were less variable than predictions of seat-on.

3.1. Seat-off

The timing difference between seat-off and the peak in AP trunk velocity ($v_{\mathrm{AP\_max}}$) had the smallest offset and variability and DWsin$(\alpha)_{\min}$ was the second best predictor of seat-off. The mean error and mean absolute error of: (1) the five single estimates, (2) the estimate based on all five features and (3) the estimate based on the features with the lowest mean absolute error ($v_{\mathrm{AP\_max}}$ and DWsin$(\alpha)_{\min}$) are presented in table 1. As can be seen, the last model yielded the best results, with a negligible mean error and the smallest absolute error of 49 ms.

The best two single predictors and the model using the best two predictors were used in the leave-one-out cross-validation. The mean error and the mean absolute error are shown in table 2. The best predictor was the model using the best two predictors, with a mean error of 0 ms and mean absolute error of 51 ms.

3.2. Seat-on

The timing difference between seat-off and DWsin$(\alpha)_{\min}$ had the smallest offset and variability and Wsin$(\alpha)_{\min}$ was the second best predictor of seat-off. The mean error and mean absolute error of: (1) the five single estimates, (2) the model based on all five features, and (3) the estimate based on the features with the lowest mean absolute error (DWsin$(\alpha)_{\min}$ and Wsin$(\alpha)_{\min}$) are presented in table 3. The combined models did not improve the first prediction using only DWsin$(\alpha)_{\max}$, which had a negligible mean error and an absolute error of 124 ms.

The best two single predictors and the model using the best two predictors were used in the leave-one-out cross-validation. The mean error and the mean absolute error are shown in table 4. The best predictor was DWsin$(\alpha)_{max}$, with a mean error of –3 ms and mean absolute error of 127 ms.

Table 3. Mean (SD) values of the error and absolute error of the seat-on estimates based on single predictors and the model combining all predictors (ms).

	DWsin $(\alpha)_{\max}$	Wsin $(\alpha)_{\min}$	$\omega_{\max}$	$v_{\text{AP\_min}}$	$v_{\text{V\_min}}$	Combined all	Combined optimal
Mean error (ms)	0 (157)	0 (213)	0 (171)	0 (311)	0 (261)	0 (170)	0 (166)
Mean abs error (ms)	124 (101)	159 (144)	133 (112)	324 (130)	233 (146)	135 (108)	130 (105)

Table 4. Mean (SD) values of the error and absolute error of the seat-on estimates based on single predictors and the model combining the two best predictors in the cross-validation (ms).

	DWsin$(\alpha)_{\max}$	Wsin$(\alpha)_{\min}$	Combined optimal
Mean error (ms)	−3 (163)	0 (221)	−3 (176)
Mean abs error (ms)	127 (105)	163 (150)	136 (113)

4. Discussion

4.1. Automated approach of STS quantification

In this study, a method was developed to estimate seat-off and seat-on in the STS task based on a single-body-fixed sensor system placed on the trunk. Six features of the trunk movement during seat-off and seat-on were calculated automatically. In two trials of the OA, the automatic analysis failed. Both trials were removed manually. In this regard, a fully automated approach has not yet been realized.

4.2. Seat-off prediction

Estimation of seat-off was successful with a mean error of the optimal model during the cross-validation of 0 ms and a mean absolute error of 51 ms (see table 2). In our study, the mean total duration of the STS was 1670 ms. Based on the durations measured in this study, the absolute estimation error for the final model of seat-off was 3.1% of the total STS duration.

The mean maximum AP velocity is the parameter closest in time to the seat-off (see figure 4). Bernardi *et al* (2004) used the peak AP velocity to define the end of the flexion momentum phase, referring to Riley *et al* (1991). In these studies, the peak AP velocity is also close to seat-off. The maximum angular velocity (see figure 4) precedes the AP velocity. The angular velocity of the trunk generates the momentum, which is necessary to displace the CoM from the chair to the feet.

The timing and the order of occurrence of events identified during STS was almost identical for the young and older adults (see figure 4). This could indicate that the strategy was similar. It could also be explained by the fact that the STS is a constrained movement. The standard deviation of the timing of these events relative to seat-off was higher in the OA than in the YA (see figure 4).

We found only one previous study aimed at validating seat-off detection (McGibbon *et al* 2004). In that study, predictions were based on signals of a force plate underneath the subject's feet, a method that would be less applicable in practice given the costs involved. Moreover, only healthy subjects with a mean age of 31 years were included. The overall absolute error was 4.5 ms. Hence, we can conclude that McGibbon's method is more precise. However in our study, young and older adults living in a care home were included and a single-body-fixed sensor system was used, which may be more versatile and suitable for clinical applications. Aissaoui *et al* (2011) used the minimum of the cross-product between the angular velocity and linear acceleration vectors to determine the seat-off instant. The seat-off instant occurs earlier, by 87 ms on average, with respect to McGibbon's model. With our approach, the absolute error of the instant of seat-off detection is 51 ms.

Maximum AP velocity appears to be the best predictor of the seat-off. What can we learn from this result for clinical practice? Several authors (e.g. Riley *et al* 1991) showed that the CoM moves forward and slightly downward during a successful STS transition. After seat-off, the CoM moves upward. This trajectory could explain why the AP velocity is the best predictor of seat-off. Manckoundia *et al* (2006) showed that during STS, Alzheimer's disease subjects reduced their forward displacement and started their upward displacement earlier than healthy elderly subjects. This resulted in poor STS quality. Thus, one possible clinical interpretation is that a dynamic trunk flexion, resulting in AP displacement of the CoM, might be a prerequisite for successful seat-off.

4.3. Seat-on prediction

Estimation of seat-on was successful with a mean error of the optimal model during the cross-validation of –3 ms and a mean absolute error of 136 ms (see table 4). Estimation of seat-on revealed that $DWsin(\alpha)_{\max}$ (−3 and 127 ms) is a better predictor than the combined features (see table 4). In our study, the mean total duration of the stand-to-sit was 1845 ms. Based on the durations measured in this study the absolute estimation error for the best predictor of seat-off was 6.9% of the total STS duration.

The timing of the mean values during STS shows several differences. All trunk features of the YA occurred before seat-on and in the OA half of the mean features occurred after seat-on. The order of the appearance of the features also differed between the young and older adults. In particular, the minimum AP velocity ($v_{\mathrm{AP\_min}}$) was an early feature in the YA, but occurred close to seat-on in the OA. This may be explained by differences in movement strategy between the two age groups.

To improve the prediction of the seat-on, separate models could be developed for different age groups in the future. However, at present, this would require arbitrary choices regarding age thresholds in application of the estimation procedure and therefore such an approach can only be developed when recordings over a wide range of ages become available.

4.4. Variance and STS strategies

The estimation error of the seat-on is markedly greater than the estimation error of the seat-off. A possible explanation for this can be found in the difference in execution (see figure 4). Apparently, the OA use different strategies for stand-to-sit, compared to the YA, which could negatively influence the prediction. Inspection of the videos supports this observation. Ageing is accompanied with the loss of automation and physical capabilities due to decreasing coordination, force and confidence. These age-associated changes may lead to modified stand-to-sit strategies, which might affect the magnitude of the variance of STS movement. Although the variance is used in the method as a weighting factor, differences in the execution of the STS contribute to the variance of the estimates. Future research should focus on the effect of different STS strategies (Doorenbosch *et al* 1994, Hughes *et al* 1996, Papa and Cappozzo 2000, Mazzà *et al* 2004, Manckoundia *et al* 2006, Scarborough *et al* 2007).

4.5. Leave-one-out methodology

In estimating the accuracy of the prediction, one would like to have an estimate with low offset and low variance. The accuracy (offset) is less important than the variance of the estimate or in other words, the precision (Kohavi 1995). McGibbon *et al* (2004) used the hold-out method to validate estimates of seat-off. This method uses a subset of the test sample for learning and a subset for testing. The hold-out method makes inefficient use of the data (Kohavi 1995). Therefore, in this study, all data were used in the model to estimate accuracy. The differences in the standard deviation of the mean error and the mean absolute error between the model and the cross-validation were very small (see table 1–4). This implies that estimation errors were not very different for subjects that were not a part of the group that the model was based on, implying that the prediction will be valid for new subjects.

4.6. Limitations

In this study, a small number of young and older adults were measured. With larger subject groups, stratified models for age and possibly for other variables such as gender could be developed in the future. In interpreting the results presented, it must be realized that the switches do not yield perfect estimates of the seat-off and seat-on events, which contributes to the estimation errors reported. Other methods of detection of seat-off (e.g. Aissaoui *et al* 2011, McGibbon *et al* 2004) could be compared in future studies to the method we have developed.

5. Conclusions

The present results demonstrate that seat-off and seat-on in a repeated sit-to-stand (STS) task can be estimated based on a semi-automatic procedure in young and older adults using a single-body-fixed sensor system with a precision of about 51 and 127 ms, respectively. The use of the ambulatory instrumentation is feasible for non-technically trained personnel. This is an important step in the development of an automated method for the quantification of STS movements in clinical practice.

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