Chair Rise Transfer Detection and Analysis Using a Pendant Sensor: An Algorithm for Fall Risk Assessment in Older People

Wei Zhang, G. Ruben H. Regterschot, Fabian Wahle, Hilde Geraedts, Heribert Baldus and Wiebren Zijlstra

Abstract—**Falls result in substantial disability, morbidity, and mortality among older people. Early detection of fall risks and timely intervention can prevent falls and injuries due to falls. Simple field tests, such as repeated chair rise, are used in clinical assessment of fall risks in older people. Development of on-body sensors introduces potential beneficial alternatives for traditional clinical methods. In this article, we present a pendant sensor based chair rise detection and analysis algorithm for fall risk assessment in older people. The recall and the precision of the transfer detection were 85% and 87% in standard protocol, and 61% and 89% in daily life activities. Estimation errors of chair rise performance indicators: duration, maximum acceleration, peak power and maximum jerk were tested in over 800 transfers. Median estimation error in transfer peak power ranged from 1.9% to 4.6% in various tests. Among all the performance indicators, maximum acceleration had the lowest median estimation error of 0% and duration had the highest median estimation error of 24% over all tests. The developed algorithm might be feasible for continuous fall risk assessment in older people.**

I. INTRODUCTION

Approximately one in three people over the age of 65 fall each year, resulting in significant physical and emotional cost on the individual and their family[1]. Older people suffering from serious injuries due to falls may lose their mobility, which has a dramatic impact on the quality of their lives[2]. An early detection of increased fall risk may allow timely interventions and reduce falls or injuries resulting from falls significantly[3]. Chair rise performance is influenced by the leg strength and power and measured as an indicator of fall risk status in older people[4], [5]. Functional tests, such as Timed-Up-Go (TUG), Five-Times-Sit-to-Stand and single chair rise test are usually incorporated in clinical fall risk assessments[6]–[8]. However, the aforementioned functional tests are only applied in controlled setups under the supervision of clinical professionals. Completion time and subjective evaluation of the difficulty when completing the test are the performance indicators. The development of on-body sensors facilitates studies in fall risk assessments beyond traditional clinical setup and measurements[6], [9]–[11]. Sensor-based chair rise assessment provides additional objective performance indicators besides the completion time. For example, peak power of a sit-to-stand (STS) transfer is measured using body-fixed sensors consisting of an accelerometer, a gyroscope and a magnetometer[9]. Fair to excellent agreements of transfer peak power measured with a standard method using force-plate and body-fixed sensors is presented. Other STS transfer performance indicators obtained from on-body sensors reported in previous studies include duration, velocity, maximum jerk, maximum acceleration and frequency features of accelerations[10]–[12]. The performance of the chair rise transfer can be measured with one or multiple sensors fixed on the body. For example, in study [12], STS timing is determined by a pair of sensors attached to the chest and the thigh. In [10], [11], [13], sensors fixed at the chest, one side of the hip and the center of mass (COM) are used to measure maximum acceleration, jerk and duration. To better understand the progression of fall risk and provide accurate assessment, prospective longitudinal studies in community settings are needed[2]. A low-cost easy-to-use fall risk assessment tool is desirable from this research perspective.

In our study, we investigate a single pendant-worn sensor for chair rise transfer detection and analysis for continuous fall risk assessment. The light-weighted sensor device can be worn with a necklace belt in front of the chest unrestrictedly as illustrated in Fig.1. We expect that the pendant sensor may improve the compliance in daily use for older people, which is important for continuous monitoring the progress and effectiveness of the intervention. This article is organized as follows. Section II introduces the data collection experiments carried out in the study. Section III describes the automatic chair rise transfer detection and performance analysis algorithm. Evaluation results are presented in section IV. In section V, we discuss the observations and conclude the study.

This research is supported by ZonMw (project number 40-00812-98-09014). ZonMw is the Netherlands organization for health research and development.

W. Zhang is with Philips Research Europe, High Tech Campus 34, 5656AE, Eindhoven, The Netherlands (phone: +31(0)611582397; e-mail: wei.zhang01@philips.com)

G. R. H. Regterschot is with University of Groningen, University Medical Center Groningen, Center for Human Movement Sciences, the Netherlands (e-mail: g.r.h.regterschot@med.umcg.nl)

F. Wahle was with Department of Knowledge Engineering, Maastricht University, the Netherlands (e-mail:fabian.wahle@googlemail.com)

H. Geraedts is with University of Groningen, University Medical Center Groningen, Center for Human Movement Sciences, the Netherlands (h.a.e.geraedts@med.umcg.nl)

H. Baldus is with Philips Research Europe, the Netherlands (heribert.baldus@philips.com)

W. Zijlstra is with University of Groningen, University Medical Center Groningen, Center for Human Movement Sciences, the Netherlands and Institute of Movement and Sport Gerontology, German Sport University Cologne, Germany (zijlstra@dshs-koeln.de)

Figure 1. Pendant-worn sensor.

II. Experiment

Three experiments were carried out during the study. The subjects considered for the study had to meet the following criteria: age between 70 and 85, community-dwelling or in assisted living conditions, able to stand up from a chair and walk for at least 10 meters. Using a cane or walker for assistance of moving was allowed during the experiments.

In the first experiment, subjects were instructed to perform several activities following a standard protocol. The protocol included: sit-to-stand (STS), sit-to-walk (STW), lying, sitting, standing, shuffling, turning, bending over, getting up from and going down to the floor, walking and going up and down stairs. Depending on the health status of the subject, a number of repetitions in each movement were performed. The subjects followed the protocol with their comfort speed. In the second experiment, the subjects performed daily living activities inside and outside of their homes for about 30 minutes without a guidance of a protocol. The subjects were allowed to perform activities of their own choice (for example, house cleaning) and with their comfort speed. In the third experiment, several controlled chair rise tests were performed. First, the subjects were asked to perform STS and STW with their own comfort speed. If they experienced no difficulty, then they were asked to perform the STS and STW as fast as possible. Up to 5 repetitions in STS and up to 3 repetitions of STW were performed from the same chair. The subjects were allowed to stop the data collection at any time in all three experiments.

In the first two experiments, a video camera was used to record the activities continuously during the data collection. A timestamp at the occurrence of each activity was annotated. In the third experiment, only the controlled STS and STW tests were annotated. The start and end time of each chair rise transfer was extracted manually by an experienced researcher for evaluation of the transfer performance.

III. Algorithm

A. Signal Processing and Feature Computation

A 3D accelerometer (50Hz) and an air pressure sensor (25Hz) were deployed in the pendant sensor device (dimension: ca. 6.5 x 4.0 x 1.2 cm, weight: 40 g). The air pressure data (*Press*) were converted into altitude (*Alt*) using Equation 1. Norm of the acceleration (*AccNorm*) was computed according to Equation 2. The raw 3D acceleration and altitude data were stored on a micro SD card in the device and processed offline. The pendant sensor device can continuously record for about 2.5 days before recharging.

Example data of a STW are illustrated in Fig.2. A chair rise transfer happened between second 1 and 3, followed by walking steps. The upper plot demonstrated the 3D acceleration (colored) and the norm of the acceleration (dotted black). A 2nd order butter-worth low-pass filter with a cut-off frequency of 3Hz was applied[10]. The filtered signal (*AccNormLPF*) (solid black) removed the high frequency noise from the raw acceleration signal. The altitude (*Alt*) signal was smoothed with a median filter with window size (*wSz*) of 1 second. The black and red lines in the lower plot of Fig.2 illustrated the original and the median filtered altitude (*AltMedF*) signals.

$$Alt = 44330 \cdot [1 - (Press/101325)^{0.19}] \quad (1)$$

$$AccNorm(t) = |Acc_x^2(t) + Acc_y^2(t) + Acc_z^2(t)| \quad (2)$$

A template of acceleration norm of a chair rise transfer was plotted as a function of time in Fig.3[14]. At the beginning of a transfer, the trunk first exhibits a forward and downward tilt to position the center of mass from the middle of the chair closer to the feet. Then the trunk starts rising up till the upright position at the end of the transfer. The *AccNormLPF* first reaches the maximum (Acc_{max}) during the accelerating phase at the beginning of rising up and then goes down to the minimum (Acc_{min}) during decelerating when the trunk moves towards the upright position. The *AccNormLPF* is close to the gravity level of 9.8m/s^2 at the start (Acc_{start}) and the end (Acc_{end}) of the transfer. The altitude rises up while the trunk is rising up and stays at an increased level while the trunk remains in an upright position, standing or walking, after the transfer.

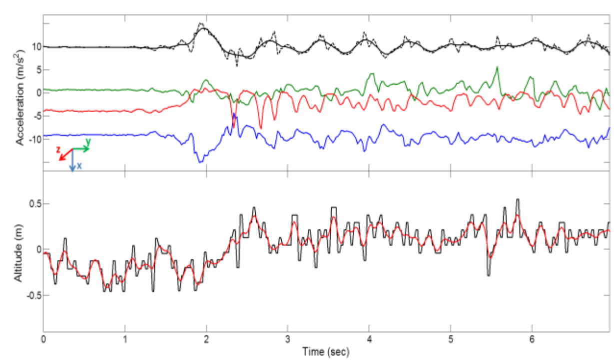

Figure 2. 3D acceleration and altitude signal of STW.

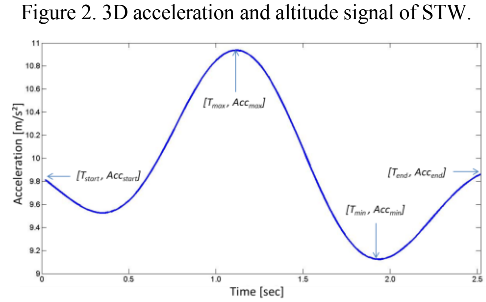

Figure 3. Norm of acceleration of a chair rise transfer.

A sliding window of 2.5 seconds length was applied to the continuous data sequence for feature extraction. Six features derived from acceleration and altitude signals were computed.

1) Maximum value of the cross correlation.

The cross correlation was used to measure the similarity between the unknown signal and the template[15]. The maximum value of the cross correlation estimation between the *AccNormLPF* and the chair rise transfer template illustrated in Fig. 3 was computed. An analytical threshold was applied to select the windows whose *AccNormLPF* have high similarity to the template. Further feature computation and classification continued with the selected windows.

2) Time difference between the maximum and the minimum acceleration.

The time difference (T_{diff}) between the T_{max} and T_{min} was computed.

3) Signal intensity before T_{start}.

Signal intensity indicates the acceleration magnitude of the body movement. *Intensity* is defined in Equation 3, where SD stands for standard devidation and *wSz* is 1 second. Signal intensity before T_{start} was computed as the median *Intensity* within 2 seconds before T_{start}, where T_{start} is the time index of the beginning of the sliding window.

$$Intensity(t)=SD[AccNormLPF(t\text{-}wSz/2{:}t+wSz/2)]. \quad (3)$$

4) Distance to the last activity.

A threshold-based filter was applied to detect the active periods in the data where activities, such as shuffling or walking, were present. An experimental threshold on the signal intensity was used. The distance to the last active period was estimated by the difference between T_{start} and the time index of the latest activity $T_{lastAct}$.

5) Altitude change

Altitude change (Alt_{diff}) is defined in Equation 4. The mean value of *AltMedF* within 2 seconds before T_{start} and 2 seconds after T_{end} was used to derive a reliable measure of altitude level. The transfer end T_{end} was determined by the time index of the first sample in *AccNormLPF* to be found back to gravity level after the Acc_{min}.

$$Alt_{diff}=\text{mean}[AltMedF(T_{end}{:}T_{end}+wSz)]-\text{mean}[AltMedF(T_{start}\text{-}wSz{:}T_{start})]. \quad (4)$$

6) Sensor Orientation

While the sensor stays quietly or during low activity, the *AccNorm* measures the gravity. The orientation of the sensor can be estimated by estimating the angle between the single axis and the norm of the acceleration. The angle between the z-axis and the vertical direction at T_{start} was estimated using Equation 5.

$$Angle(t)=\arccos[Acc_z(t)/AccNorm(t)]\cdot(180^o/\pi). \quad (5)$$

B. Classification

Chair rise transfers (positive instance) and other movements (negative instance) were extracted from the data collected in the first experiment. A Support Vector Machine (SVM) with a Gaussian kernel function was trained to distinguish chair rise transfers from the other movements[16]. The kernel parameter γ and the soft margin C were optimized in the 5-fold cross validation to minimize the misclassification rate[17].

C. Chair Rise Transfer Performance Indicator

Several performance indicators (PIs) which were studied in literature have been introduced in Chapter I. In the earlier studies, transfer duration, maximum acceleration, peak power and maximum jerk have demonstrated their sensitivities and reliabilities in evaluating chair rise performance in old people[10], [11], [18]. We incorporated these four PIs in the chair rise performance analysis algorithm.

1) Duration

Duration was the time difference between the transfer start T_{start} and end T_{end}.

2) Maximum Acceleration

Maximum acceleration was the maximum value Acc_{max} in the *AccNormLPF* excluding the gravity between T_{start} and T_{end}.

3) Peak power

Power exertion was computed as the product of the force (F) and the vertical velocity (V_{vert})[9], where $F=BodyMass*AccNormLPF$ and V_{vert} was the integration of the vertical acceleration due to motion (*AccNormLPF* excluding the gravity) from T_{start} [18]. The maximum power exertion of the transfer was defined as the peak power.

4) Maximum jerk

Jerk was the 1st derivative of the *AccNormLPF*. Maximum jerk was the maximum value in jerk between T_{start} and T_{max} (the time index of Acc_{max}).

IV. Results

A. Validation of Transfer Detection in Standard Protocol

We measured the performance of chair rise detection with recall, precision and F-score (harmonic mean of recall and precision)[19]. 211 positive instances and 570 negative instances were extracted from 21 subjects (4 males and 17 females, age: 78.5±5.4) in the first experiment. The average performance of the 5-fold cross validation was 85.3% recall and 87.4% precision. The F-score was 0.86.

B. Evaluation of Transfer Detection in Daily Life Activity

The detection algorithm was evaluated further with the data of 30 subjects (6 males and 24 females, age: 78.8±5.2) in the second experiment. The length of recorded activities was 24.8±7.8 minutes, within which 128 chair rise transfers were annotated. 78 transfers were detected. 10 other movements were falsely detected as chair rise. The performance was 60.9% recall, 88.6% precision and an F-score of 0.72 in daily life activity.

C. Transfer Detection and PI Estimation in Different Conditions

In total 40 subjects (14 males and 26 females, age: 81.7±5.6, weight: 79.1±14.1 kg, height: 1.65±0.1 m) participated in the third experiment, in which all subjects performed tests of STS and STW with their comfort speed. A subgroup of 26 subjects performed STS and a subgroup of 17 subjects performed STW with fast speed. For this controlled experiment, only the transfer detection rate, same as the recall, was computed. In total 982 transfers were annotated, in which 882 were detected. The detection rate was 88.8% over all tests. For each detected chair rise transfer, the PIs were automatically estimated. Meanwhile, the PIs of the detected transfers were estimated by the researcher using the manually extracted transfer timing.

Estimation error was defined in Equation 6. The boxplots in Fig.4 indicate the estimation error of PIs over all tests. The median estimation error of PIs in all transfers was 24.1% for duration, 2.6% for peak power, 0 for maximum acceleration and maximum jerk.

$$Error=100\cdot|PI_{manual}-PI_{automatic}|/PI_{manual}. \quad (6)$$

Table 1 summarizes the chair rise transfer detection and PIs estimation in the individual tests. The number of the subjects, the number of the annotated transfer, the detection rate (DR%) and the median, mean and standard deviation of estimation error of the PIs are listed.

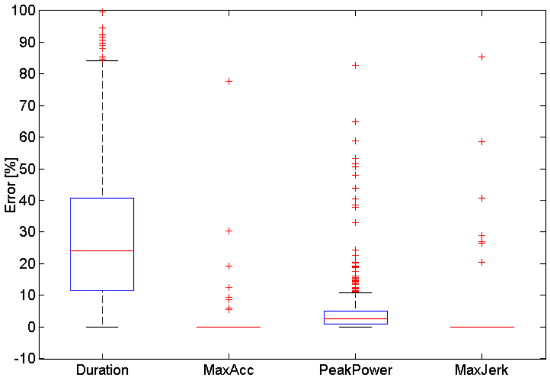

Figure 4. Estimation error of chair rise performance indicators.

TABLE 1. EVALUATION OF TRANSFER DETECTION AND PERFORMANCE INDICATOR ESTIMATION IN DIFFERENT CHAIR RISE CONDITIONS.

	STS Comfort	STS Fast	STW Comfort	STW Fast
Nr Subject	40	26	40	17
Nr Transfer	390	255	235	102
DR%	90.0	90.1	88.0	86.3
Estimation error Median/Mean±SD(%)				
Duration	15.9/ 17.7±14.4	33.9/ 35.6±23.0	28.1/ 27.8±16.9	46.1/ 47.5±23.7
Max Acc	0	0/ 0.5±5.7	0/ 0.2±1.3	0
Peak Power	1.9/ 4.1±8.2	2.6/ 3.3±4.3	3.3/ 4.1±6.4	4.6/ 5.0±4.6
Max Jerk	0	0/ 1.2±13.9	0/ 1.0±7.3	0

V. DISCUSSION AND CONCLUSION

In this study, we developed an automatic chair rise detection and analysis algorithm using a pendant-worn sensor device. The automatic detection was evaluated in transfers performed by older people following a standard protocol, as well as in daily life activities. The performance was estimated with recall, precision and F-score. The algorithm detected over 85% of the chair rise transfers in the standard protocol. However, only 61% of the chair rise in daily life was detected. The decreased detection recall in daily life may be explained by the difference between the movement pattern of chair rises observed in the experiment following a standard protocol and chair rises happening in daily life. In the former case, subjects usually completed the transfers with full attention and clean movement. In the latter case, a larger variance in the movement pattern may be introduced by the interference from other movements, for example turning while rising up from a chair, which were not observed in the data collected following the standard protocol. The algorithm had good detection precision in both standard protocol and daily life, which were 87% and 89% respectively. From the fall risk assessment point of view, in trade-off of a lowered recall, a higher precision was preferable as it would provide certain confidence that the fall risk was monitored and assessed based on true chair rise transfers.

The automatic estimation of the performance indicators of chair rise transfers were evaluated in various controlled tests in older people. The algorithm could reliably estimate maximum acceleration and maximum jerk in most of the chair rise transfers, except in a few outliers. These two indicators were less sensitive to the detection accuracy of the start and the end of a transfer. In some cases, the acceleration peaks induced by the stepping right after the chair rise were falsely detected as the maximum acceleration of the transfer, which might explain some of the outliers in the error of maximum acceleration in STW. Median estimation error in peak power ranged between 1.9% in STS with comfort speed and 4.6% in STW with fast speed. Since the integration interval for power estimation was from the start of the transfer, the accuracy of the peak power estimation was influenced by the determination of the transfer timing. Peak power was usually seen before Acc_{min} was reached. Hence, the detection of the transfer end had minor impact on the peak power estimation. Compared to the peak power, duration had larger estimation error, which implied that false detection of the transfer end was mainly responsible for the duration estimation error. Chair rise transfer peak power is sensitive in detecting change in leg strength and power[10] and has good test retest reliability[11], [18]. The relatively small error of automatic estimation in peak power implied that peak power could be a useful parameter for continuous fall risk assessment. In the on-going studies, fall risk assessment in daily life based on chair rise performance measured using the pendant sensor will be evaluated in field trials.

In conclusion, the developed pendant-sensor based algorithm could detect chair rise transfers in daily life with good precision and reliably estimate transfer peak power. The pendant-worn sensor might be feasible for continuous fall risk assessment and monitoring in old people.

REFERENCE

[1] M. E. Tinetti, M. Speechley, and S. F. Ginter, "Risk factors for falls among elderly persons living in the community," *N. Engl. J. Med.*, vol. 319, no. 26, pp. 1701–1707, Dec. 1988.

[2] C. Ni Scanaill, C. Garattini, B. R. Greene, and M. J. McGrath, "Technology Innovation Enabling Falls Risk Assessment in a Community Setting," *Ageing Int.*, vol. 36, no. 2, pp. 217–231, Jun. 2011.

[3] T. E. Shubert, M. L. Smith, L. P. Prizer, and M. G. Ory, "Complexities of Fall Prevention in Clinical Settings: A Commentary," *The Gerontologist*, p. gnt079, Jul. 2013.

[4] J. F. Bean, D. K. Kiely, S. Herman, S. G. Leveille, K. Mizer, W. R. Frontera, and R. A. Fielding, "The relationship between leg power

and physical performance in mobility-limited older people," *J. Am. Geriatr. Soc.*, vol. 50, no. 3, pp. 461–467, Mar. 2002.

[5] M. C. Perry, S. F. Carville, I. C. H. Smith, O. M. Rutherford, and D. J. Newham, "Strength, power output and symmetry of leg muscles: effect of age and history of falling," *Eur. J. Appl. Physiol.*, vol. 100, no. 5, pp. 553–561, Jul. 2007.

[6] S. R. Lord, H. B. Menz, and A. Tiedemann, "A physiological profile approach to falls risk assessment and prevention," *Phys. Ther.*, vol. 83, no. 3, pp. 237–252, Mar. 2003.

[7] A. L. Hendrich, P. S. Bender, and A. Nyhuis, "Validation of the Hendrich II Fall Risk Model: a large concurrent case/control study of hospitalized patients," *Appl. Nurs. Res. ANR*, vol. 16, no. 1, pp. 9–21, Feb. 2003.

[8] M. E. Tinetti, "Performance-oriented assessment of mobility problems in elderly patients," *J. Am. Geriatr. Soc.*, vol. 34, no. 2, pp. 119–126, Feb. 1986.

[9] W. Zijlstra, R. W. Bisseling, S. Schlumbohm, and H. Baldus, "A body-fixed-sensor-based analysis of power during sit-to-stand movements," *Gait Posture*, vol. 31, no. 2, pp. 272–278, Feb. 2010.

[10] G. R. H. Regterschot, M. Folkersma, W. Zhang, H. Baldus, M. Stevens, and W. Zijlstra, "Sensitivity of sensor-based sit-to-stand peak power to the effects of training leg strength, leg power and balance in older adults," *Gait Posture*, vol. 39, no. 1, pp. 303–307, Jan. 2014.

[11] R. Regterschot, W. Zhang, H. Baldus, M. Steven, and W. Zijlstra, "Test-retest reliability of sensor-based sit-to-stand measures in young and old adults," *Gait Posture, 2014, doi:10.1016/j.gaitpost.2014.03.193.*

[12] D. Giansanti and G. Maccioni, "Physiological motion monitoring: a wearable device and adaptative algorithm for sit-to-stand timing detection," *Physiol. Meas.*, vol. 27, no. 8, pp. 713–723, Aug. 2006.

[13] M. Fujimoto and L.-S. Chou, "Dynamic balance control during sit-to-stand movement: an examination with the center of mass acceleration," *J. Biomech.*, vol. 45, no. 3, pp. 543–548, Feb. 2012.

[14] W. Zhang, H. Baldus, and S. Schlumbohm, "Sit-to-Stand Transfer Detection," WO/2013/001411, 04-Jan-2013.

[15] A. Goshtasby, S. H. Gage, and J. F. Bartholic, "A Two-Stage Cross Correlation Approach to Template Matching," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-6, no. 3, pp. 374–378, May 1984.

[16] C. J. C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," *Data Min. Knowl. Discov.*, vol. 2, no. 2, pp. 121–167, Jun. 1998.

[17] J. Platt, "Advances in kernel methods," in *Advances in kernel methods: support vector learning*, B. Schölkopf, C. Burges, and A. Smola, Eds. MIT Press, 1999, pp. 185–208.

[18] W. Zhang, G. R. H. Regterschot, H. Schaabova, H. Baldus, and W. Zijlstra, "Test-Retest Reliability of a Pendant-Worn Sensor Device in Measuring Chair Rise Performance in Older Persons," *Sensors*, vol. 14, no. 5, pp. 8705–8717, May 2014.

[19] M. Sokolova, N. Japkowicz, and S. Szpakowicz, "Beyond Accuracy, F-Score and ROC: A Family of Discriminant Measures for Performance Evaluation," in *AI 2006: Advances in Artificial Intelligence*, A. Sattar and B. Kang, Eds. Springer Berlin Heidelberg, 2006, pp. 1015–1021.