International Journal of Neurorehabilitation
ISSN: 2376-0281

Tanaka et al., Int J Neurorehabilitation Eng 2014, 1:1
DOI: 10.4172/2376-0281.1000106

Research Article Open Access

Fall-Risk Classification of the Timed Up-And-Go Test with Principle Component Analysis

Noriko Tanaka[1], Nor Aini Zakaria[2,3], Nelson Kipchirchir Kibinge[2], Shigehiko Kanaya[2], Toshiyo, Tamura[1]*, and Masaki Yoshida[1]

[1]*Department of Physical Therapy, School of Biomedical Engineering, Osaka Electro Communication University, Japan*
[2]*School of Information Science, Nara Institute of Science and Technology, Japan*
[3]*Department of Biomedical Instrumentation and Electronics, University Teknologi Malaysia, Johor, Malaysia*

Abstract

This study aimed to show that important fall risk measures among the elderly can be classified using multiple parameters obtained from wearable inertial sensors. The timed up-and-go (TUG) test, a well-known standard assessment test, was used to evaluate the risk of falling among elderly individuals. The use of wearable inertial sensors enables extraction of triaxial acceleration and angular velocity signals for offline analysis. Thirty-eight elderly patients from Fujimoto Hayasuzu Hospital participated in this study. Specific results were provided from the signals obtained from acceleration and angular velocity, and analysis was carried out in each phase of various activities, such as sit-to-stand, walking, etc. Seventy-eight parameters were obtained from the extracted acceleration and angular velocity signals in all phases to classify the risk of falling among the elderly. Using principle component analysis, the most important measures were selected from the gathered parameters. The most influential measure in differentiating subjects with high and low fall risks was the turning angular velocity signal.

Keywords: Fall; Wearable inertial sensor; TUG; Acceleration; Angular velocity; PCA

Introduction

As the elderly population continues to increase, the welfare and health care systems are also expected to expand significantly to ensure continued improvement in the elderly population's quality of life (QOL). Falls among the elderly have become a major concern; almost 30% of individuals aged 65 years and above fall each year [1-4], and most cases are unwitnessed. Falls lead to deterioration in health and physical activities; physiological distress; pain caused by injuries, impairment, or imbalanced gait; fear of repeated falling; and deterioration of QOL. Various physical assessment tools have been developed to reduce the risk of falling among the elderly [5]. One established standard assessment used by therapists worldwide to measure basic mobility function and evaluate the risk of falling among the elderly is the timed up-and-go (TUG) test. However, in classifying the risk of falling using this method, age-related ability was identified to have limited clinical value. The literature recognizes a myriad of risk factors for falls, including demographic factors, historical factors, physical deficits, environment factors, and others [6,7]. Diverse factors associated with physical deficits contribute to falling. The likelihood of falling increases with the number of risk factors. Classification of the fall risk using several important measures selected from various gathered parameters is essential to enhance interest in this topic.

In current practice, many therapists use time parameters as measured with a stopwatch to classify the risk of falling among the elderly. New sensor technology implemented by previous researchers enables extraction of acceleration and angular velocity signals for fall risk assessment. Sway and standing balance have been estimated using accelerometry and gyro-sensors. Several other gait performance measures, including the TUG test, have also been evaluated [8-21]. Various parameters have been measured and collected to classify the risk of falling among the elderly. These parameters include position and angle, angular velocity, linear acceleration step and stride, cadence, speed, energy, and frequency. The root mean square of the vertical linear acceleration has been used to measure gait smoothness, with larger values linked to an increased risk of falling. However, it is difficult to identify the parameters that most strongly influence the risk of falling. Generally, an increase in spatial and temporal variability is associated with an increased risk of falls [2]. In addition to the TUG test, several phases are available for measurement (e.g., sit-to-stand, walking turn), and knowledge of which phases and parameters are the most significant with respect to the risk of falls would be clinically beneficial.

The risk of falls is currently predicted using derived models as opposed to correlating variables with the risk or occurrence of falls. The decision tree, neural network, linear discriminate function, cluster analysis, and support vector machine have all been candidates for fall risk prediction. The stability and variability of walking can be identified by a simple control theory such as the Lyapunov exponent [22]. A review by Howcroft et al. [8] suggested that intelligent computing methods such as neural networks and Bayesian classifiers might be more appropriate for fall risk classification than regression techniques [8]. However, no studies have identified the parameters that play the most important roles in the risk of falls.

Several parameters (usually highly correlated) can be computed from the signals recorded during the test. To avoid redundancy and identify the features that are most sensitive to locomotor performance, a dimensionality reduction was performed through principal component analysis (PCA).

In this study, we performed a quantitative analysis using the dataset obtained from wireless inertial sensors during the TUG test and classified the risk of falling among elderly subjects using multivariate analysis to identify the most effective parameter. Furthermore, the result will interpret and discuss with the clinical point of view.

***Corresponding author:** Toshiyo Tamura, Department of Physical Therapy, School of Biomedical Engineering, Osaka Electro Communication University, Japan, E-mail: tamurat@isc.osakac.ac.jp

Received February 28, 2014; **Accepted** Aprile 28, 2014; **Published** May 30, 2014

Citation: Tanaka N, Zakaria NA, Kibinge NK, Kanaya S, Tamura T, et al. (2014) Fall-Risk Classification of the Timed Up-And-Go Test with Principle Component Analysis. Int J Neurorehabilitation 1: 106. doi:10.4172/2376-0281.1000106

Copyright: © 2014 Tanaka N, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

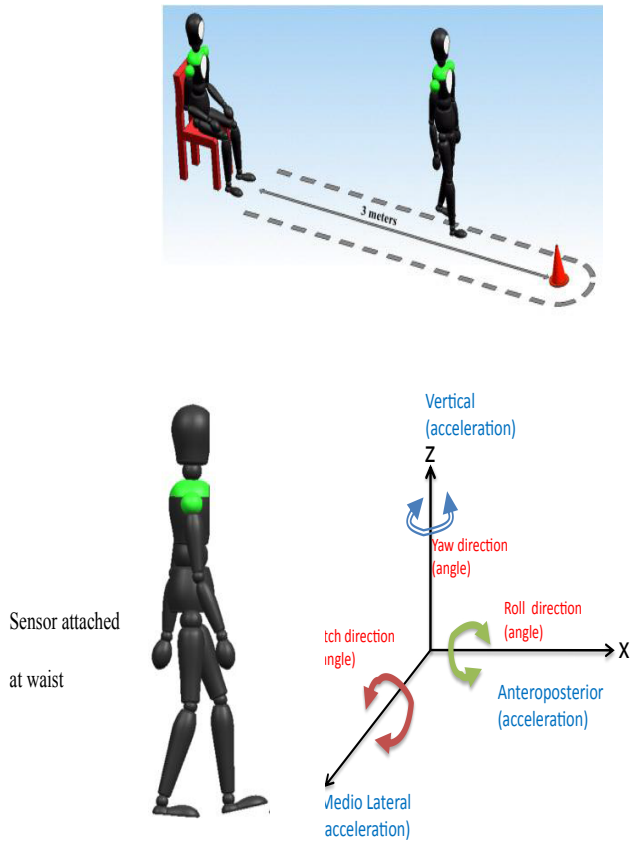

Figure 1: (a) TUG test set and (b) sensor attachment and direction of accelerometer and angular velocity.

Parameters			Sit-bend	Bend-stand	Sit-stand	Walk 1	Turn 1	Walk 2	Turn 2	stand-bend	bend-sit	stand-sit	Total	Sum
Time			1	1	1	1	1	1	1	1	1	1	1	11
RMS	Acceleration	AP	1	1		1		1		1	1			6
		ML	1	1		1		1		1	1			6
		V	1	1		1		1		1	1			6
	Angular Velocity	Roll	1	1		1		1		1	1			6
		Pitch	1	1		1		1		1	1			6
		Yaw	1	1		1		1		1	1			6
Amplitude	Angular Velocity	Pitch	1	1								1		3
		Yaw					1		1					2
	Angle	Pitch			1							1		2
Number of steps						1	1	1	1				1	5
Number of strides						1	1	1	1				1	5
Mean step time						1	1	1	1					4
Mean stride time						1	1	1	1					4
Candence						1	1	1	1					4
Speed						1		1						2
Total														78

Table 1: Parameters in each phase.

Methods

Subjects

Thirty-eight elderly subjects (male, 20; female, 18) with an average age of 65.18 ± 8.90 years from Fujimoto Hayasuzu Hospital, Japan participated in the TUG test. The low-fall-risk (LFR) group comprised 27 subjects, and the high-fall-risk (HFR) group comprised 11 subjects. Ethical approval was obtained from the Fujimoto Hayasuzu Hospital Ethics Committee. A previous study by Shumway-Cook et al. reported that the use of 13.5 s as a threshold achieved 87% sensitivity for multiple fallers and 87% specificity for nonfallers [20]. Accordingly, the subjects were categorized as LFR upon completing the test within 13.5 s, while subjects who could not complete the test within that time were classified as HFR.

Experimental set-up

This experiment was based on the TUG test, which was introduced by Podsiadlo and Richardson in 1991. Figure 1(a) shows the main principle of the TUG test.

For the sake of simplicity, the subjects wore only one inertial sensor dorsally on the waist while performing the test. The sensor was tightly attached to the waist to minimize motion artifacts. For this purpose, the sensor was slotted in a belt that was attached to the waist, as shown in Figure 1(b). Throughout the experiment, a therapist was present for safety reasons. The experiment was conducted as follows:

1. The subject sat on an armless chair with a back (approximate seat height of 46 cm).
2. The subject rose from the chair.
3. The subject began to walk toward a marked post 3 m away.
4. The subject turned after reaching the marked post.
5. The subject walked another 3 m to return to the seat.
6. The subject turned to face forward before sitting.

Signal analysis

a) Parameters selected during the TUG test

The parameters obtained from the wearable inertial sensor during the TUG test are shown in Table 1. Each phase was divided by 12 and comprised time, accelerometer, and angular velocity parameters, as well as spatial and temporal parameters, such as step and stride [23].

The first analysis involved comparison of each feature between the two groups via a t-test. The threshold was 13.5 s based on a previous study [20]. Significant parameters were then chosen, but in accordance with our aim, the time data were eliminated.

At the beginning of the study, we divided all subjects into HFR and LFR groups using the total time parameters. Due to their important influence, we removed all time parameters to determine whether other parameters could be used to correctly classify the elderly subjects into their respective groups.

b) PCA

The most important objective of PCA is to represent multivariate data as low-dimensional data. By combining the data that account for the most variation among the original multivariate data, the data are summarized with minimal loss of information. By projecting all observations onto this low-dimensional subspace and plotting the results, it is possible to visualize the structure of the dataset. From the new low-dimensional constructed principal component, the variables that contribute most to the patterns among the observations could be determined. Therefore, PCA may also frequently indicate which parameters of which variables account for the patterns among the observations. The variables that influence the pattern and the correlations among the variables in a dataset are important;-some of these low-performance variables might therefore be removed from consideration to simplify the overall analyses.

c) Preprocessing of the data

In this study, 78 parameters were collected from the signals shown in Tables 1 and 2. In total, 44 parameters were found to have significant value in differentiating the HFR and LFR groups. Of 44 significant parameters, 35 were selected (9 time parameters had been removed

	Parameter		Parameter		Parameter
P1	Time-sit-bend	P27	RMS.acc.V-sit-bend	P53	RMS.angvel.Y-walk1
P2	Time-bend-stand	P28	RMS.acc.V-bend-stand	P54	RMS.angvel.Y-walk2
P3	Time-sit-stand	P29	RMS.acc.V-stand-bend	P55	# of Step-walk 1
P4	Time-walk 1	P30	RMS.acc.V-bend-sit	P56	# of Step-walk 2
P5	Time-turn 1	P31	RMS.angvel.R-sit-bend	P57	# of Step-turn 1
P6	Time-walk 2	P32	RMS.angvel.R-bend-stand	P58	# of Step-turn 2
P7	Time-turn 2	P33	RMS.angvel.R-stand-bend	P59	# of Step-total
P8	Time-stand-bend	P34	RMS.angvel.R-bend-sit	P60	# of Stride-walk 1
P9	Time-bend-sit	P35	RMS.angvel.P-sit-bend	P61	# of Stride-walk 2
P10	Time-stand-sit	P36	RMS.angvel.P-bend-stand	P62	# of Stride-turn 1
P11	Time-total	P37	RMS.angvel.P-stand-bend	P63	# of Stride-turn 2
P12	AMP.angvel-sit-stand	P38	RMS.angvel.P-bend-sit	P64	# of Stride-total
P13	AMP.angvel-bend-stand	P39	RMS.angvel.Y-sit-bend	P65	Mean step time-Walk 1
P14	AMP.angvel-stand-sit	P40	RMS.angvel.Y-bend-stand	P66	Mean step time-Turn 1
P15	AMP.angvel Y-Turn 1	P41	RMS.angvel.Y-stand-bend	P67	Mean step time-Walk 2
P16	AMP.angvel-Y Turn 2	P42	RMS.angvel.Y-bend-sit	P68	Mean step time-Turn 2
P17	AMP.angle Y-sit stand	P43	RMS.acc.AP-walk1	P69	Mean stride time-Walk 1
P18	AMP.angle Y-stand sit	P44	RMS.acc.AP-walk2	P70	Mean stride time-Turn 1
P19	RMS.acc.AP-sit-bend	P45	RMS.acc.ML-walk1	P71	Mean stride time-Walk 2
P20	RMS.acc.AP-bend-stand	P46	RMS.acc.ML-walk2	P72	Mean stride time-Turn 2
P21	RMS.acc.AP-stand-bend	P47	RMS.acc.V-walk1	P73	Cadence-walk 1
P22	RMS.acc.AP-bend-sit	P48	RMS.acc.V-walk2	P74	Cadence -walk 2
P23	RMS.acc.ML-sit-bend	P49	RMS.angvel.R-walk1	P75	Cadence -turn 1
P24	RMS.acc.ML-bend-stand	P50	RMS.angvel.R-walk2	P76	Cadence -turn 2
P25	RMS.acc.ML-stand-bend	P51	RMS.angvel.P-walk1	P77	speed walk 1
P26	RMS.acc.ML-bend-sit	P52	RMS.angvel.P-walk2	P78	speed walk2

Where AMP is amplitude, RMS is root mean square. “angvel“ is angular velocity signal. Y, P and R are yaw, pitch and raw directions, respectively..
“acc” is acceleration signal. ML, AP and V are medio-lateral, antero-posterior, vertical directions, respectively

Table 2: Selected parameters Yellow cells indicate parameters statistically significant between the HFR and LFR groups.

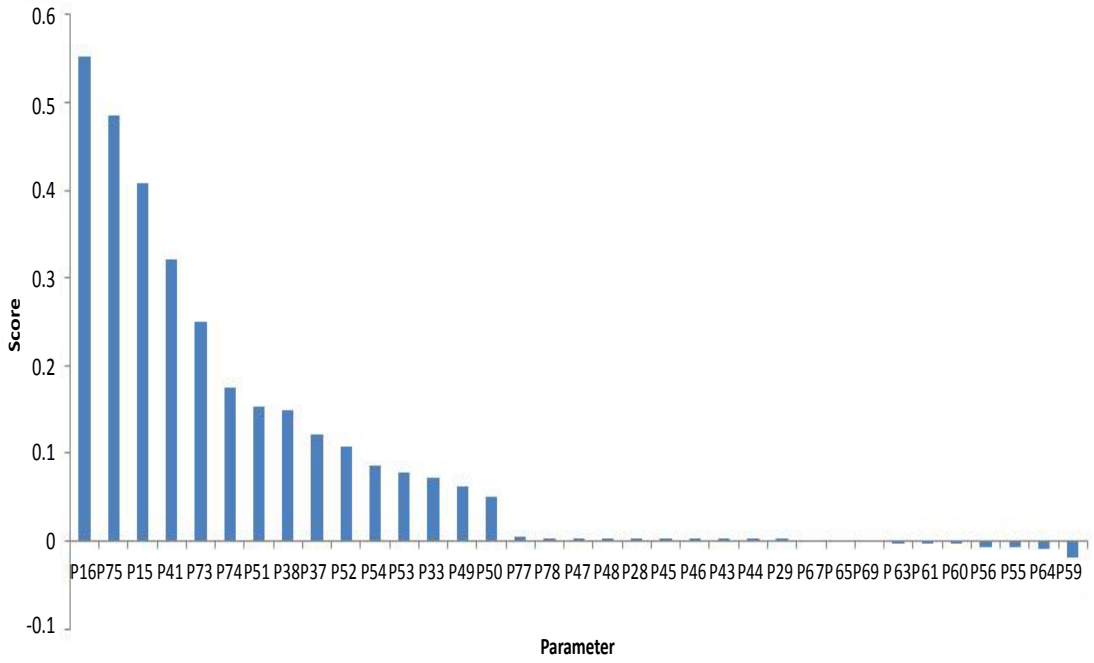

Figure 2: Linear combination of the first and second component analyses accounted for 69.92% of the variation.

from the dataset). These 35 significant parameters underwent PCA, and the parameters that influenced the data most strongly were ranked.

Results

Based on PCA of the 35 principal components, the most important parameter in PC1 was P16 (amplitude of angular velocity signal during the turn 2 phase in the yaw direction). Meanwhile, the most important parameter in PC2 was P75 (cadence parameter in the turn 1 phase). The first component contributed 49.46% of the variance to the whole dataset. PC1 is insufficient to model the systematic variation of a dataset; thus, the second component was considered. PC2 contributed 20.16% of the variance. The bar graph of each component's variance in Figure 2 shows how the first two components influenced the data. PC1 and PC2 were adequate for classification, allowing for discovery of ~70% of the variance in the dataset. In general, it was assumed that these two components explained a sufficient amount of the variance, providing a meaningful visual representation of the subjects and parameters.

Figure 3(a) and (b) use bar graphs to rank the important parameters PC1 and PC2, respectively. For PC1, the most important positive parameters were P16, P75, P15, P14, P73, P74, P51, P38, P37, P52, P54, P53, P33, P49, and P50, while the most important negative parameters were P59, P64, P55, P56, and P60. For PC2, the most important positive parameter was P75, while the most important negative parameters were P74, P73, P38, P16, P15, P41, P37, P52, P54, P51, and P53.

By projecting all observation onto the lower-dimensional subspace and plotting the results, it was possible to visualize the pattern of the 38 subjects using all 35 parameters, as illustrated in Figure 4. Using the first principal component, the subjects were distributed into two groups. The HFR subjects were plotted on the left side of the graph, and the LFR subjects were scattered throughout the right side of the graph. The subjects were classified into their respective groups relatively accurately by PC1. For PC1, the negative values influenced the classification of subjects in the HFR group, while the positive values influenced the classification of subjects in the LFR group. As seen in the figure, the HFR and LFR subjects could be classified into their respective groups with almost 100% accuracy. Therefore, the parameters listed for PC1 were used to classify the subjects.

Discussion

For fall-risk assessment, an instrumented TUG test that uses portable inertial sensors (iTUG test) has been proposed to improve the TUG test in several ways; namely, by allowing for automatic detection and separation of each performance, facilitating a detailed analysis of each and enabling a higher sensitivity than the TUG test [21,24-26]. Sensitive and reliable measures for fall-risk assessment have been provided by measurement of wearable inertial sensors [27]. These measures might be of primary interest for clinical applications [25,26]. Gait measures can be divided into three subcategories: temporal gait, range of motion, and spatial gait.

Temporal gait measures are calculated based on the time of gait events, which are often measured with a stopwatch. Wearable motion sensors calculate the cadence, stance, etc. The range of motion of the trunk segment is estimated by integrating the signals from the angular velocity sensor. Furthermore, spatial gait measures, including stride length and velocity, are estimated using a biomechanical model [27]. In our study, these measures were easily obtained from the wearable inertial sensor.

The TUG test is classified into 6 phases: sit-to-bend, bend-to-stand, walking, turning, walking, turning, stand-to-bend, and bend-to-sit and two combined phases of sit-to-stand and stand-to-sit. The selected parameters related to movement are shown in Table 1. The parameters we skipped were not strongly involved in movement. Turning speed is important, but it is difficult to estimate the turning distance; thus, the speed could not be obtained. Nevertheless, we selected 78 parameters and then 44 significant parameters; 35 parameters were ultimately selected (9 time parameters were removed). These 35 significant

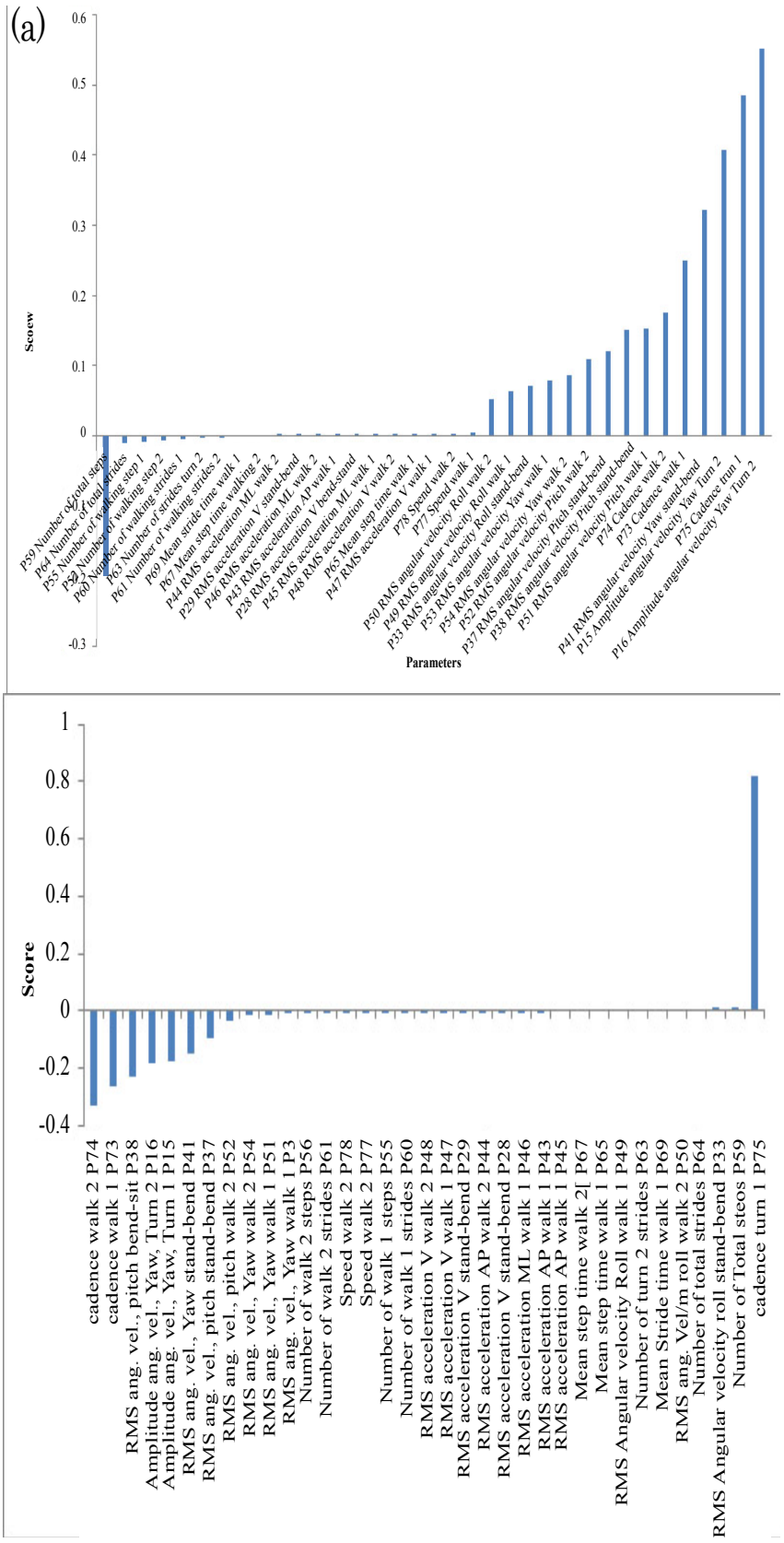

Figure 3: (a): Ranking of important parameters in PC1 using significant parameters (excluding time parameters) (b) Ranking of important parameters in PC2 using significant measures (excluding time parameters).

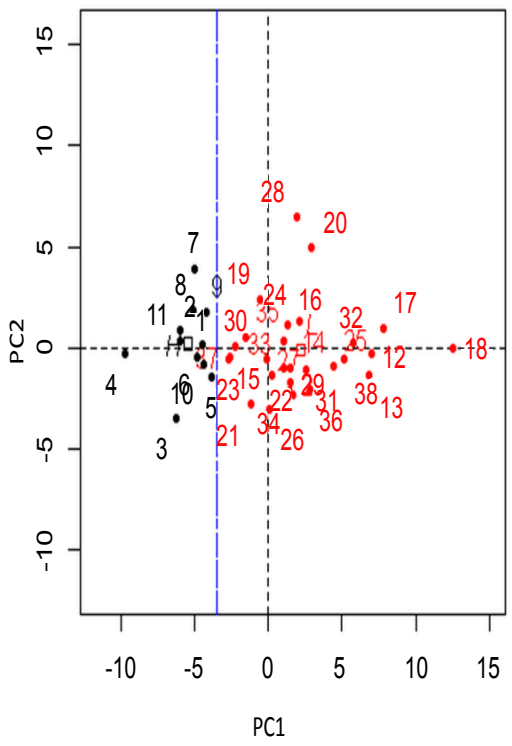

Figure 4: PCA individual factor map using significant parameters (excluding time parameters).

parameters were calculated by PCA and were found the influence for the fall risk.

The principle parameter score was the turning amplitude of the angular velocity signal during the turn phase in the yaw direction. The turn-to-sit movement is a combination of the turning and stand-to-sit transition, and is the most important and difficult task for elderly individuals whose physical activity has declined. PCA clearly showed the distribution of the HFR and LFR subjects. The peak angular velocity of the trunk during the turn-to-sit transition was important [24-28].

The TUG test includes performance of several movements and provides objective measures related to the four major components of the test: gait, turning, sit-to-stand, and turn-to-sit. The gait measures include the cadence, gait cycle, stride, and stance. Our analysis indicated high scores for cadence (P73 and P74), amplitude of the angle (P15 and P16), and speed (P77 and P78). Subjects in the HFR group showed slower speeds and smaller cadences. Furthermore, the root mean squares of the angular velocity in the roll (P14 and P15), pitch (P51 and P52), and yaw (P53 and P54) directions had higher ranks.

With respect to turning, the tuning duration, number of steps, peak tuning velocity, and step time are important measures [27]. Our results followed above clinical measures some extend and clearly showed the significance of the amplitude of the angular velocity.

During the stand-to-sit and sit-to-stand movements, the root mean squares of the angular velocities in the roll, pitch, and yaw directions played important roles. A previous study showed that frail elderly subjects exhibited significantly decreased smoothness in the sit–stand transition pattern [8,21,23,29-33].

In conclusion, we aimed to identify the most important parameters during the TUG test using PCA. The principle component was angular velocity in the yaw direction, and the second principle component was the cadence of turning. Furthermore, in each phase; i.e., sit-to-stand, walking, turning, and turn-to-sit, we determined the principle component scores, which are significant measures of the risk of falling. We attempted a simple PCA analysis and the results were in agreement with previous quantitative research. Thus we found that PCA could easily estimate a simple measure for fall risk in TUG.

Acknowledgement

This work was supported in part by a grant-in-aid from the Regional Innovation Strategy Support Program, 2011–2015.

References

1. Hornbrook MC, Stevens VJ, Wingfield DJ, Hollis JF, Greenlick MR, et al. (1994) Preventing falls among community-dwelling older persons: results from a randomized trial. Gerontologist 34: 16-23.
2. Hausdorff JM, Rios DA, Edelberg HK (2001) Gait variability and fall risk in community-living older adults: a 1-year prospective study. Arch Phys Med Rehabil 82: 1050-1056.
3. Swanenburg J, de Bruin ED, Uebelhart D, Mulder T (2010) Falls prediction in elderly people: a 1-year prospective study. Gait Posture 31: 317-321.
4. Thrane G, Joakimsen RM, Thornquist E (2007) The association between timed up and go test and history of falls: the Tromsø study. BMC Geriatr 7: 1.
5. Yang CC, Hsu YL (2010) A review of accelerometry-based wearable motion detectors for physical activity monitoring. Sensors (Basel) 10: 7772-7788.
6. Studenski S, Wolter L (1998) Instability and falls. In: Duthie EH Jr, Katz PR, eds. Practice of Geriatrics. 3d ed. Philadelphia: Saunders, 199-206.
7. Tinetti ME, Doucette J, Claus E, Marottoli R (1995) Risk factors for serious injury during falls by older persons in the community. J Am Geriatr Soc 43: 1214-1221.
8. Howcroft J, Kofman J, Lemaire ED (2013) Review of fall risk assessment in geriatric populations using inertial sensors. J Neuroeng Rehabil 10: 91.
9. Lindemann U, Hock A, Stuber M, Keck W, Becker C (2005) Evaluation of a fall detector based on accelerometers: a pilot study. Med Biol Eng Comput 43: 548-551.
10. Bourke AK, O'Donovan KJ, Olaighin G (2008) The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls. Med Eng Phys 30: 937-946.
11. Noury N, Rumeau P, Bourke AK, Ólaighin G, Lundy JE (2008) A proposal for the classification and evaluation of fall detectors. IRBM 29: 340-349.
12. Bourke AK, O'Brien JV, Lyons GM (2007) Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait Posture 26: 194-199.
13. Karantonis DM, Narayanan MR, Mathie M, Lovell NH, Celler BG (2006) Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Trans Inf Technol Biomed 10: 156-167.
14. Bourke AK, Lyons GM (2008) A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. Med Eng Phys 30: 84-90.
15. Dinh A, Shi Y, Teng D, Ralhan A, Chen L, et al. (2009) A fall and near-fall assessment and evaluation system. Open Biomed Eng J 3: 1-7.
16. Kangas M, Konttila A, Lindgren P, Winblad I, Jämsä T (2008) Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait Posture 28: 285-291.
17. Kangas M, Vikman I, Wiklander J, Lindgren P, Nyberg L, et al. (2009) Sensitivity and specificity of fall detection in people aged 40 years and over. Gait Posture 29: 571-574.
18. Sixsmith A, Johnson N (2004) A smart sensor to detect the falls of the elderly. IEEE Pervasive Computing 3: 42-47.
19. Caby B, Kieffer S, de Saint Hubert M, Cremer G, Macq B (2011) Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry. Biomed Eng Online 10: 1.

20. Shumway-Cook A, Brauer S, Woollacott M (2000) Predicting the probability for falls in community-dwelling older adults using the Timed Up & Go Test. Phys Ther 80: 896-903.

21. Higashi Y, Yamakoshi KT, Fujimoto T, Sekine M, Tamura T (2008) Quantitative evaluation of movement using the timed up-and-go test. IEEE Eng Med Biol Mag 27: 38-46.

22. Toebes MJ, Hoozemans MJ, Furrer R, Dekker J, van Dieën JH (2012) Local dynamic stability and variability of gait are associated with fall history in elderly subjects. Gait Posture 36: 527-531.

23. Zakaria NA, Kuwae Y, Tamura T, Minato K, Kanaya S (2013) Quantitative analysis of fall risk using TUG test. Comput Methods Biomech Biomed Engin .

24. Salarian A, Horak FB, Zampieri C, Carlson-Kuhta P, Nutt JG, et al. (2010) iTUG, a sensitive and reliable measure of mobility. IEEE Trans Neural Syst Rehabil Eng 18: 303-310.

25. Zampieri C, Salarian A, Carlson-Kuhta P, Aminian K, Nutt JG, et al. (2010) The instrumented timed up and go test: potential outcome measure for disease modifying therapies in Parkinson's disease. J Neurol Neurosurg Psychiatry 81: 171-176.

26. Zampieri C, Salarian A, Carlson-Kuhta P, Nutt JG, Horak FB (2011) Assessing mobility at home in people with early Parkinson's disease using an instrumented Timed Up and Go test. Parkinsonism Relat Disord 17: 277-280.

27. APDM mobility lab. http://apdm.com/gait-and-posture/Mobility-Lab/ Accessed on 20 Feb 2014.

28. Salarian A, Russmann H, Vingerhoets FJ, Dehollain C, Blanc Y, et al. (2004) Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring. IEEE Trans Biomed Eng 51: 1434-1443.

29. Marschollek M, Nemitz G, Gietzelt M, Wolf KH, Meyer Zu Schwabedissen H, et al. (2009) Predicting in-patient falls in a geriatric clinic: a clinical study combining assessment data and simple sensory gait measurements. Z Gerontol Geriatr 42: 317-321.

30. Najafi B, Aminian K, Loew F, Blanc Y, Robert PA (2002) Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. IEEE Trans Biomed Eng 49: 843-851.

31. Schurr K, Sherrington C, Wallbank G, Pamphlett P, Olivetti L (2012) The minimum sit-to-stand height test: reliability, responsiveness and relationship to leg muscle strength. Clin Rehabil 26: 656-663.

32. Ganea R, Paraschiv-Ionescu A, Büla C, Rochat S, Aminian K (2011) Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people. Med Eng Phys 33: 1086-1093.

33. Bagalà F, Klenk J, Cappello A, Chiari L, Becker C, et al. (2013) Quantitative description of the lie-to-sit-to-stand-to-walk transfer by a single body-fixed sensor. IEEE Trans Neural Syst Rehabil Eng 21: 624-633.