Wii Balanced Board-Based Utilization for the Human Body Center of Pressure for the Falling Detection via Multivariate Empirical Mode Decomposition and Multivariate Multi-scale Entropy

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Abstract: Center of pressure (COP) evaluation is one of important parameters in the fall detection algorithm for the elder people. The Wii balance board (WBB) (Nintendo Co., Ltd., Redmond, WA 98052), originally an accessory of a game controller for the Wii video game console, is a potential device that can be utilized for the human balance evaluation system. Initially, this study evaluates the WBB signal in comparison to the AMTI (Advanced Mechanical Technology Inc., Newton, MA, USA) as the reference. Initially, the experiment is conducted for three different conditions; open eye, close eye and one-foot stand for five volunteers. The mean of correlation coefficient between WBB and AMTI is over 0.98 on X-direction and over 0.99 on Y-direction. The multivariate multi-scale entropy (MMSE) and multivariate empirical mode decomposition (MEMD) are used for the signal feature evaluations. The results show that complexity indexes (CI) from the MSE-based algorithms have significant results only between young and elderly groups and young and elderly-fall groups. However, there are no significant differences on between elderly and elderly-fall groups. In conclusion, this study shows that the WBB can be applied as the balance-measuring device. Meanwhile, further investigations need to be conducted for the advanced algorithms to fall detection for the elderly people.

Key words: Center of pressure, Wii balance board, multivariate multi-scale entropy, multivariate empirical mode decomposition, complexity index.

1. Introduction

Falling is one of the crucial concerns for the elderly. Figuring out the chance of fall from the elderly could be essentially important for the fall detection condition. In further, the human balance evaluation by investigating the center of pressure (COP) is fundamental in fall detector [1], [2]. The body movement will affect the anterior-posterior (A-P) and medial-lateral (M-L). Several studies have been conducted for the balance analysis. A study about the relationship of the center of gravity of body position and the COP has been conducted by Benda et al. [3]. Recently, Lu et al. utilized the accelerometer sensor for the COP evaluation [4].

For the balance evaluation, the balance measurement system should be well investigated. The most of the balance-measuring devices are economically expensive and physically heavy. The Wii balance board (WBB) is originally an accessory of a game controller for the Wii video game console. It was developed by on July 2007 by Nintendo (Nintendo Co., Ltd., Redmond, WA 98052). Several studies have evaluated the utilization of WBB. McGough et al. investigated the real-time weight bearing asymmetry [5]. Gil-Gómez et al. utilized the WBB for the acquired brain injury [6]. Meanwhile, Young, W et al. used the WBB for the standing balance [7]. In advanced, Huurnink et al. conducted a WBB-based study for the postural investigation with the COP evaluation [8].

Our study has two major parts; the device and the balance-related algorithms. The WBB is utilized as the balance-measuring machine with comparison to the AMTI (Advanced Mechanical Technology Inc., Newton, MA, USA) as the reference. The multivariate multi-scale entropy (MMSE) and multivariate empirical mode decomposition (MEMD) are used for the signal feature evaluations.

2. Device, Experimental Design and Methods

The dimension of WBB is relatively portable; 511mm x 316mm x 53.2mm respectively for the width, length and depth. WBB is powered by four AA-size batteries and has four 16-bit pressure sensors, marked by S1, S2, S3 and S4 as shown on Fig.1. The program interface developed by Japanese Rehabilitation Tool Study Group (http://www.eonet.ne.jp/~rpt/) is used for the data collection via Bluetooth connection. This program is able to save A/P-direction and M/L-direction signals, and draw COP. For the actual location, the ratio should multiply the size of balance board. The length between the sensors are 42cm and 24cm. Meanwhile, the center of WBB is zero that left to right is -21 to 21cm and top to bottom is -12 to 12cm. The evaluation of the COP is calculated as follows;

$$Kx = \frac{S1+S2}{S3+S4} \tag{1}$$

$$Ky = \frac{S1+S4}{S2+S2} \tag{2}$$

$$COPx = \frac{Kx-1}{Kx+1} * (-21) \tag{3}$$

$$\mathrm{COPy} = \frac{Ky-1}{Ky+1} * (-12) \tag{4}$$

Fig. 1. Wii balanced board sensors.

For the experimental result comparison of the WBB, the AMTI is utilized for the reference as shown on Fig. 2. AMTI can evaluate three moments and three forces for the X-Y-Z axes by the following equations;

$$COPx = \frac{My+Fx*Z_0}{Fz} + X_0 \quad (5)$$

$$COPy = \frac{Mx+Fy*Z_0}{Fz} + Y_0 \quad (6)$$

where the F_x, F_y and F_z are the forces from each axis, respectively. Furthermore, the Mx, My and Mz are the moments from each axis, respectively. The X_o and Y_o are the initial positions from the subject and Z_o is the top of the plate.

Five volunteers are involved to conduct three different conditions; open eye, close eye and one-foot stand. Each condition will be repeated for five times for every volunteer. The correlation coefficient for X- and Y-axis are evaluated.

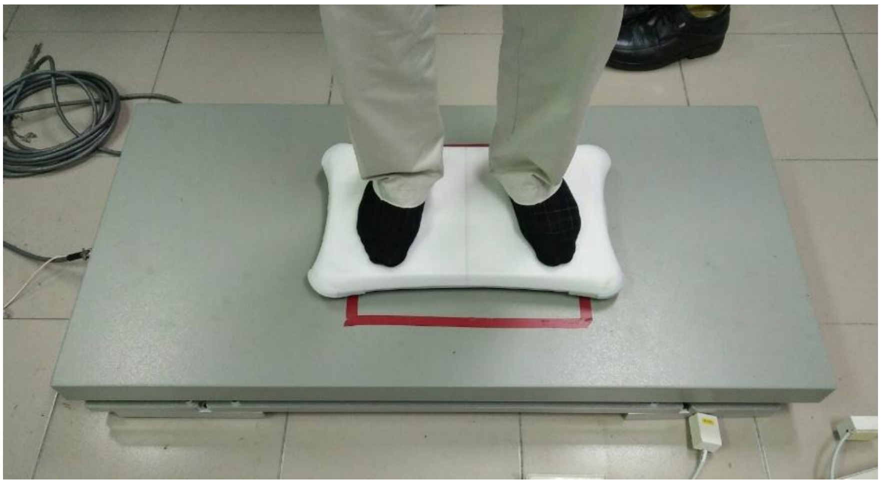

Fig. 2. Comparing WBB and AMTI.

The first applied algorithm is the multivariate multi-scale entropy (MMSE). Initially Richman et al. proposed the sample entropy (SE) for analyzing the complex system [9] and the modified SE, namely MSE, multi scale entropy [10], the MMSE is proposed [11]. The time series $\{y^{(\tau)}\}$ is reconstructed with the scale factor, τ. For the evaluation of the COP complexity, the complexity index (CI) is evaluated by calculating the area under MSE curve.

For the filtering algorithm, the empirical mode decomposition (EMD) is utilized. EMD is applied for the non-linear and non-stationary signal [12]. It works by finding the local minima and maxima in order to generate the lower and upper envelopes, respectively. It also will decompose the original time series data to several intrinsic mode functions (IMFs). The EMD equation is shown as following;

$$X(t) = \sum_{i=1}^{n} c_i + r_n \quad (7)$$

where $X(t)$ is the original signal, c_i is the *i*-IMF and r_n is the residual.

However, the original EMD algorithm has the mode mixing problem. The ensemble EMD (EEMD) was developed by Wu et al. to overcome the mode mixing problem by adding the noise to the original signal [13]. In advanced, the multivariate EMD (MEMD) is working by not only adding the noise, but also evaluating the multivariate input signal [14] and has the advantages to the multi-channel signal [15]. The modified MMSE, MEMD-enhanced MMSE, is further evaluated. This study originally proposed by [16]. The MEMD-enhanced MMSE works by replacing the course graining-based time series to C_n which is equation (12) or equation (13).

$$C_n = \sum_{j=n}^{J} c_j \tag{8}$$

$$C_n = \sum_{j=1}^{J-n+1} c_j \tag{9}$$

where the MEMD decomposes the original time series into the number of IMFs, c_j denotes j-th IMF and n is [1, j].

3. Result and Discussion

Via the comparison result between WBB and AMTI signal, it can be seen in Fig. 3. The correlation coefficient for both WBB and AMTI is evaluated for different conditions as shown in Tables 1-3. The experiment is conducted for three different conditions; open eye, close eye and one-foot stand for five volunteers. The mean of correlation coefficient between WBB and AMTI is over 0.98 on X-direction and over 0.99 on Y-direction. In order to compare the MMSE and the MEMD-enhanced MMSE algorithms, the IMF 4 to IMF 7 are selected to the constructed signal. For the visualization, the comparisons are shown in Figs. 4-6. For the statistical analysis, the t-test evaluation is utilized to evaluate the CI as shown in Table 4 for 14 young, 47 elderly, and 23 elderly-fall volunteers. The results show that complexity indexes from the MSE-based algorithms have significant results ($P<0.05$) only between young and elderly groups, and young and elderly-fall groups. However, there is no significant difference between elderly and elderly-fall groups.

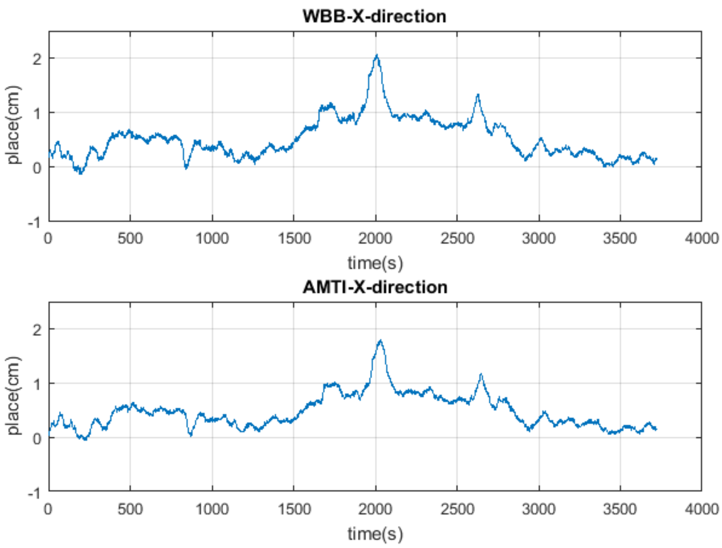

Fig. 3. Resampled X-direction signals comparison between WBB and AMTI.

Table 1. Correlation Coefficient between WBB and AMTI – Open Eye

Volunteer	X	Y
A	0.981±0.011	0.995±0.002

B	0.987±0.009	0.990±0.006
C	0.969±0.013	0.991±0.006
D	0.978±0.007	0.992±0.006
E	0.965±0.027	0.987±0.010
Average mean ± SD	0.978±0.008	0.992±0.004

Table 2. Correlation Coefficient between WBB and AMTI – Close Eye

Volunteer	X	Y
A	0.995 ±0.001	0.995 ±0.004
B	0.971 ±0.028	0.992 ±0.013
C	0.977 ±0.011	0.995 ±0.003
D	0.979 ±0.010	0.991 ±0.009
E	0.947 ±0.023	0.985 ±0.004
Average mean ± SD	0.976 ±0.018	0.990 ±0.007

Table 3. Correlation Coefficient between WBB and AMTI – One Foot Standing

Volunteer	X	Y
A	0.990 ±0.007	0.993 ±0.004
B	0.987 ±0.007	0.996 ±0.001
C	0.985 ±0.012	0.996 ±0.002
D	0.985 ±0.020	0.994 ±0.003
E	0.937 ±0.116	0.992 ±0.009
Average mean ± SD	0.980 ±0.022	0.994 ±0.005

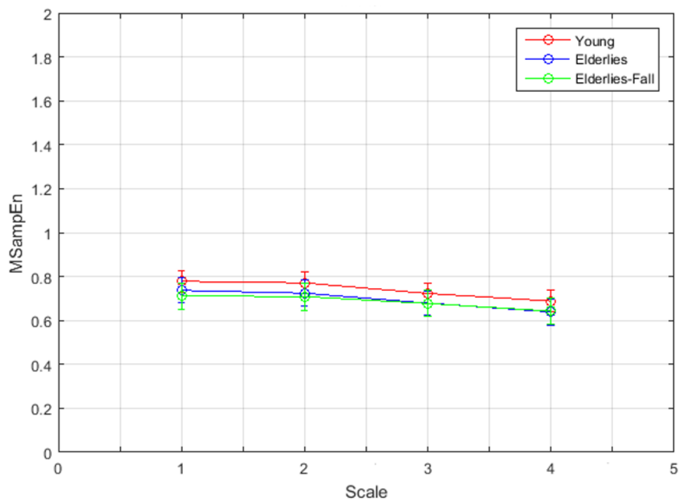

Fig. 4. MMSE IMF 4 to 7 with m = 2, r = 0.15.

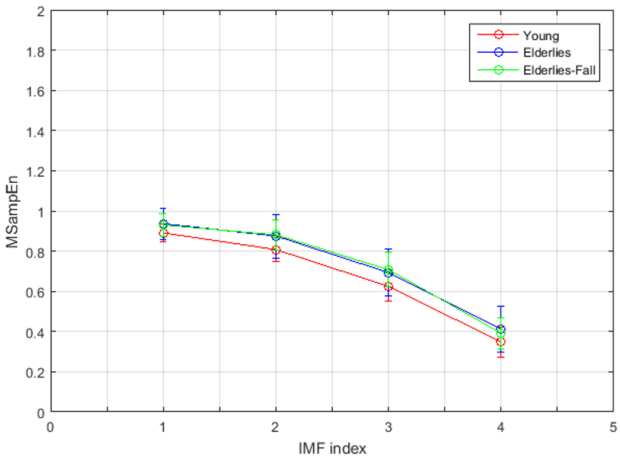

Fig. 5. MEMD-enhance MMSE uses equation (8) and IMF 4 to 7 with m = 2, r = 0.15.

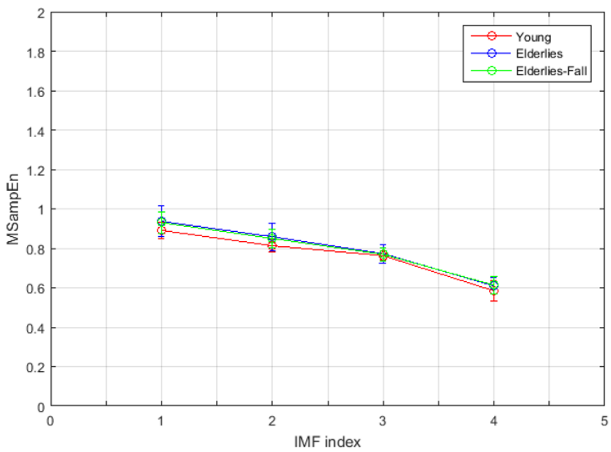

Fig. 6. MEMD-enhance MMSE uses equation (9) and IMF 4 to 7 with m = 2, r = 0.15.

Table 4. Statistical Results between Each Group for 14 Young, 47 Elderly, and 23 Elderly-Fall Volunteers

Methods	Young vs. Elderly	Young vs. Elderly-Fall	Elderly vs. Elderly-Fall
MMSE	5.77E-05	1.41E-05	0.169
MEMD-enhanced MMSE equation (8)	4.78E-04	5.60E-06	0.443
MEMD-enhanced MMSE equation (9)	5.59E-04	1.61E-05	0.308

4. Conclusion

In conclusion, this study shows that the WBB can be applied as the balance-measuring device. Meanwhile, the results show that complexity indexes from the MMSE and MEMD-enhanced MMSE algorithms have significant results only between young and elderly groups, and young and elderly-fall groups. However, there is no significant difference between elderly and elderly-fall groups. Further investigations need to be conducted for the advanced algorithms to fall detection for the elderly people. Also, the number of volunteers should be increased to prove which algorithms are more suitable to fall detection.

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