Performance evaluation of acceleration and jerk in unstable walking detection

N R Nurwulan¹ and G Selamaj²

¹Department of Industrial Engineering, Sampoerna University, Jl. Raya Pasar Minggu Kav. 46, Pancoran, Jakarta 12780, Indonesia
²Department of Economics, Universiteti Ismail Qemali, Skelë, Rruga Kosova, Vlorë 9401, Albania

E-mail: nurul.nurwulan@sampoernauniversity.ac.id

Abstract. Accelerometers have been widely used for human activity recognition as an early prediction of fall risk. However, acceleration data do not consider the force of gravity. Recent studies found that jerk, the derivative of acceleration, can describe the changes of body accelerations without considering the sensor orientation. This might overcome the issues caused by the displacement of the sensor, especially if a smartphone-based accelerometer is used as the sensor. This study aimed to compare the performance of acceleration and jerk in detecting postural stability using the postural stability index (PSI). Slightly different daily activity living such as walking on a flat surface, walking upstairs, and walking downstairs were chosen to compare the sensitiveness of acceleration and jerk in detecting the slight postural sway in healthy subjects. The collected data were pre-processed using the 8-modes of ensemble empirical mode decomposition (EEMD). Then, the multiscale entropy (MSE) of each intrinsic mode function (IMF) was calculated, and in the end, the PSI values were obtained. The paired t-test calculation using acceleration data showed that walking on a flat surface and walking downstairs are significantly different (p = 0.039). Whereas, the jerk dataset could not distinguish walking on a flat surface and walking downstairs (p = 0.228). From this result, it is evident that acceleration is better in recognizing human activities than jerk.

1. Introduction

Injury, illnesses, and old age could be the causes of unstable walking or the inability to maintain stability when walking. The treatment of the unstable walking could be too late due to the difficulty to notice this problem. The unstable walking could develop to fall if it is left untreated. Fall is common in older adults, approximately 30% of older adults experience falls annually [1]. Not only older adults, young adults are also at risk of falls, especially if they have injured themselves in the past or have postural-related illnesses [2-3]. Young adults are at higher risk of falls if they have a motor disability [3]. The impact of falls could increase both physical and mental health issues [4]. Thus, it is important to prevent falls by detecting unstable walking as early as possible.

Since the unstable walking is difficult to notice due to the fact that the sway in the postural stability of healthy subjects is not as significant as the subjects with illnesses, the determination of healthy subjects with falling risk could be difficult. In 2019, Nurwulan et al. [5] proposed the postural stability index (PSI), a measurement to distinguish the unstable walking in healthy subjects, as an early detection tool to recognize the potential risk of falls in healthy subjects. The PSI was developed by decomposing
the raw accelerometer signal data using the ensemble empirical mode decomposition (EEMD) into six intrinsic mode functions (IMFs), then the complexity index of each IMF is calculated using the multiscale entropy (MSE) method. The PSI itself is constructed by dividing the value of the complexity index from the dominant IMF with the total complexity index of all IMFs [5 - 6].

The most common device in human activity recognition is an accelerometer. This is because an accelerometer is cheap, simple, and easy to use. In addition, it also provides an objective measurement for human daily activities. Although the inertial measurement unit (IMU) accelerometer can provide a sensitive result, the accelerometer built-in smartphone gained more popularity due to its simplicity [7].

We can collect the acceleration data from the smartphone by simply putting the accelerometer inside of the pocket of the subject. Regardless of this practicality, the smartphone-based accelerometer might give inaccurate results due to the possibility of the displacement of the smartphone when it is inside of the pocket. Past studies proposed to use jerk, the derivative of the acceleration, to overcome the displacement issues of the sensor [8]. Using jerk, it is possible to monitor the sensor orientation when the sensor is frequently shifted.

Influenced by the satisfying results of the past studies in employing jerk for human activity, the aim of this current study was to evaluate the performance comparison between jerk and acceleration in detecting unstable walking in healthy young adults. The walking activities without obstacles, namely normal walking, walking upstairs, and walking downstairs were chosen with the consideration these activities have subtle differences. By evaluating the performance of jerk and acceleration in detecting subtle changes in walking activities, it can be seen whether it is true that jerk is better than acceleration for human daily activity recognition. The current paper is organized as follows. The description of the dataset used and the literature review is written in the Methodology section. Section 3 presents the results and discussions of the findings. Ultimately, the conclusion is presented in section 4.

2. Methodology

We used the public domain dataset available in Kaggle by Malekzadeh et al. [7]. The accelerometer used in the data collection was the built-in accelerometer in the iPhone 6s. The smartphone was put inside of the pocket of the subjects and the sampling frequency was set to 50 Hz. A total of 24 young adults with ages ranging from 18 to 46 years old were recruited to participate in the study. The subjects were asked to perform human daily activity tasks. For the comparative analysis in this study, we chose normal walking, walking downstairs, and walking upstairs as the activities considering they have slight differences. Before calculating the PSI values, the collected acceleration data were decomposed using the 8-modes of EEMD and the complexity index of each IMF was calculated using the MSE [5-6].

2.1. Acceleration and jerk

In terms of direction and speed, acceleration is the derivative of the velocity, which is the rate of change of velocity. Nowadays, acceleration is widely used in human activity recognition and it is the most common tool. Regardless of its popularity, acceleration neglects the force of gravity and thus, it is more like the consequence of a static load [9]. Jerk is the rate of change of acceleration, it is the second derivative of the velocity. Jerk is believed to be able to solve the displacement problem of the sensor orientation when the smartphone is shifted in the pocket of the subjects because the magnitude of the jerk is representing the differences in accelerations independently from the orientation of the sensor [8].

2.2. Ensemble empirical mode decomposition

Ensemble empirical mode decomposition (EEMD) is a strong noise-assisted method for the nonstationary and nonlinear signals such as acceleration data [10]. This method could overcome the drawbacks of the former empirical mode decomposition (EMD) method. In the EEMD, the white noise is added to the original signal before the decomposition of the signal into several layers of intrinsic mode functions (IMFs). The decomposed signal data are then averaged and each layer of IMF is obtained. In
this current study, we used 8-modes of EEMD with 1 mode is the original signal, 6 modes of IMFs, and 1 mode is the residual.

2.3. Multiscale entropy

Multiscale entropy (MSE) has been widely used in the biomedical field [5-6, 11-13] due to its ability in explaining the complexity phenomenon in human physiological data. The complexity of the physiological data can be quantified by constructing the consecutive coarse-grained.

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \leq j \leq \frac{N}{\tau}$$ \hspace{1cm} (1)

where $\tau$ is the scale factor and $N/\tau$ is the length of each coarse-grained time series. Subsequently, the sample entropy is then calculated for each of the coarse-grained time series plotted as a function of the scale factor. Finally, the complexity index (CI) is obtained by summing up all of the sample entropy values.

2.4. Postural stability index

The postural stability index (PSI) was proposed to distinguish the postural sway in the unstable movement of healthy subjects. The postural sway is barely recognizable in healthy subjects, unlike the postural sway in subjects with illnesses. The PSI can be used as an early detection tool to determine the unbalanced movement in healthy subjects. The PSI is constructed by dividing the complexity index value of the dominant IMF by the total complexity indexes. The dominant IMF in the PSI is IMF3, with the consideration that the frequency of the IMF3 is close to the walking frequency [5-6].

$$PSI = \frac{CI \text{ of IMF3}}{CI \text{ of IMF1} + CI \text{ of IMF2} + \cdots + CI \text{ of IMF6}}$$ \hspace{1cm} (2)

3. Results and discussion

The current research examined slightly different human daily tasks undertaken by young and healthy subjects, including normal walking, walking downstairs, and walking upstairs. The aim of using slightly different daily tasks to compare the sensitivity of acceleration and jerk in discriminating slightly different tasks. Table 1 shows the values of the calculated PSI of each task performed by the subjects.

The PSI of normal walking (average of 0.299±0.100) is lower than walking downstairs (average of 0.340±0.064) and walking upstairs (average of 0.305±0.116). The trend of the PSI values in each subject, however, varies. Most of the subjects showed a U-shaped trend with walking upstairs as either with the lowest or the highest PSI value. For instance, subjects 1, 4, 11, 18, 22, and 24 showed a U-shaped trend with normal walking as the highest PSI value. Whereas, subject 2, 5, 8, 9, 12, 19, and 20 showed a U-shaped trend with normal walking as the lowest PSI value. The rest of the subjects showed either an increasing or decreasing trend. Subjects 3 and 7 showed an increasing trend with walking downstairs with the lowest PSI value. Meanwhile, subject 6, 10, 13, 14, 16, and 21 showed a decreasing trend with walking downstairs has the highest PSI, and walking upstairs has the lowest PSI value.
Table 1. Calculated postural stability index

| Subject | Acceleration | Jerk |
|---------|--------------|------|
|         | Downstairs  | Normal | Upstairs | Downstairs | Normal | Upstairs |
| 1       | 0.330        | 0.543  | 0.429    | 0.175      | 0.273  | 0.298    |
| 2       | 0.387        | 0.241  | 0.245    | 0.220      | 0.245  | 0.257    |
| 3       | 0.318        | 0.320  | 0.547    | 0.381      | 0.317  | 0.479    |
| 4       | 0.275        | 0.298  | 0.196    | 0.234      | 0.259  | 0.194    |
| 5       | 0.307        | 0.223  | 0.471    | 0.286      | 0.328  | 0.285    |
| 6       | 0.351        | 0.191  | 0.117    | 0.217      | 0.257  | 0.212    |
| 7       | 0.333        | 0.348  | 0.378    | 0.278      | 0.267  | 0.304    |
| 8       | 0.344        | 0.203  | 0.363    | 0.267      | 0.449  | 0.112    |
| 9       | 0.351        | 0.289  | 0.367    | 0.324      | 0.314  | 0.287    |
| 10      | 0.375        | 0.308  | 0.289    | 0.328      | 0.295  | 0.235    |
| 11      | 0.309        | 0.358  | 0.275    | 0.165      | 0.217  | 0.247    |
| 12      | 0.278        | 0.224  | 0.302    | 0.180      | 0.302  | 0.236    |
| 13      | 0.366        | 0.283  | 0.173    | 0.341      | 0.302  | 0.222    |
| 14      | 0.264        | 0.239  | 0.090    | 0.206      | 0.245  | 0.188    |
| 15      | 0.292        | 0.230  | 0.270    | 0.322      | 0.255  | 0.332    |
| 16      | 0.339        | 0.256  | 0.212    | 0.274      | 0.339  | 0.188    |
| 17      | 0.431        | 0.252  | 0.315    | 0.215      | 0.190  | 0.267    |
| 18      | 0.553        | 0.578  | 0.493    | 0.362      | 0.786  | 0.214    |
| 19      | 0.415        | 0.353  | 0.446    | 0.458      | 0.094  | 0.260    |
| 20      | 0.304        | 0.204  | 0.315    | 0.237      | 0.390  | 0.285    |
| 21      | 0.299        | 0.226  | 0.200    | 0.210      | 0.263  | 0.216    |
| 22      | 0.335        | 0.382  | 0.281    | 0.221      | 0.318  | 0.275    |
| 23      | 0.359        | 0.235  | 0.272    | 0.302      | 0.283  | 0.134    |
| 24      | 0.253        | 0.390  | 0.268    | 0.227      | 0.237  | 0.279    |

As for the calculation of the PSI value using jerk data, normal walking (average of 0.301±0.123) had a higher value than walking upstairs (average of 0.250±0.072) and walking downstairs (average of 0.268±0.073). The PSI calculation using jerk data also showed a similar trend as the acceleration data. Most subjects showed a U-shaped trend. For instance, subjects 3, 7, 15, 17, and 19 showed a U-shaped trend with normal walking as the lowest PSI value. Whereas, subjects 4, 5, 6, 8, 12, 14, 16, 18, 20, 21, and 22 showed a U-shaped trend with normal walking as the highest PSI value. The rest of the subjects showed either an increasing or decreasing trend. Subject 1, 2, 11, and 24 showed an increasing trend with walking upstairs as the highest PSI value. Subject 9, 10, 13, and 23 showed a decreasing trend with walking downstairs as the highest PSI value.

In terms of difficulty, normal walking is supposed to be the most balanced movement because there are no obstacles in performing normal walking. Regarding the average values of the PSI based on acceleration data, it can be seen that the balance is associated with a low PSI value. Conversely, for the PSI calculation using jerk data, balance is associated with a high PSI value. Therefore, using the acceleration data, walking downstairs is the least balanced movement. Meanwhile, based on jerk data, walking upstairs is the least balanced movement. From the difficulty point of view, normal walking is...
an easier task compared to walking downstairs and walking upstairs because normal walking requires
the least balance skills. Past studies found that subjects with neurological disorders, poor balance, and
poor grip strength showed difficulty in either walking downstairs or walking upstairs [14]. Walking
upstairs is more demanding because the movement is against gravity. Whereas, walking downstairs
is more challenging and often associated with the risk of falls because the movement is getting additional
acceleration from gravity. In order to overcome the challenges of walking downstairs and walking
upstairs, people normally walk slower [14-16].

| Table 2. Paired t-test evaluation of the PSI values |
|-----------------------------------------------|
| Paired t-test | Acceleration | Jerk |
|---------------|--------------|------|
| Activities    |              |      |
| Normal - Downstairs | 1-tailed | 0.020 | 0.114 |
|                | 2-tailed    | 0.039 | 0.228 |
| Normal - Upstairs | 1-tailed | 0.401 | 0.057 |
|                | 2-tailed    | 0.801 | 0.114 |
| Upstairs - Downstairs | 1-tailed | 0.062 | 0.173 |
|                | 2-tailed    | 0.123 | 0.346 |

With regard to the calculation of the PSI values, it is rather difficult to see the differences between
tasks. Thus, the paired t-test was used to confirm whether there is a significant difference between tasks.
Based on Table 2, only the acceleration data can show the significant difference between normal walking
and walking downstairs. Conversely, the jerk data could not be used to differentiate the activities since
there is no significant difference between activities. The interesting fact that we found from the analysis
is that the t-test evaluation could not show the difference between walking upstairs and walking
downstairs, even though the average PSI values for each task seem different. In addition, the normal
walking and walking upstairs using either acceleration or jerk data cannot be discriminated by the PSI.
This could be caused by the sampling rate in this study is 50 Hz, relatively higher compared to the
sampling rate of 20 Hz in the past study [5-6]. Comparative studies showed that a low sampling rate is
more sensitive to detect human daily activities [17-18]. Future studies evaluating the effect of the
sampling rate might give a better understanding of detecting unstable walking. Additionally, revising
the PSI might also be able to distinguish human daily activities better [19].

4. Conclusion

The current study compared the performance of both acceleration and jerk data in distinguishing walking
activities in healthy subjects using the postural stability index (PSI). The aim of this study was to analyze
the sensitivity of both acceleration and jerk data to discriminate human daily activities with slight
differences. With regards to the calculation results using paired t-test evaluation, jerk data could not
distinguish the walking activities. In contrast, we found a significant difference in normal walking and
walking downstairs using acceleration data. Based on the calculation of the PSI values, walking
downstairs is the least stable movement amongst the other walking activities. Young adults could
perform walking upstairs better than walking downstairs, regardless of the fact that both walking tasks
are equally challenging than normal walking. This may be caused by there is an additional acceleration
from gravity when we walk downstairs. Ultimately, it can be concluded that the acceleration performs better than jerk data in terms of human activity recognition.

5. References

[1] Fletcher PC and Hirdes JP 2004 Restriction in activity associated with fear of falling among community-based seniors using home care services Age Ageing vol 33 p 273-279
[2] Lo J and Ashton-Miller JA 2008 Effect of upper and lower extremity control strategies on predicted injury risk during simulated forward falls: A study in healthy young adults J Biomech. Eng. vol 2008 p 041015
[3] Severino A, Moriarty A and Playford D 2014 The risk of falling in young adults with neurological conditions: A systematic review Disabil. Rehabil. vol 36 p 963-977
[4] Stevens JA, Ballesteros MF, Mack KA, Rudd RA, deCaro E and Adler J 2012 Am. J. Prev. Med. vol 43 p 59-62
[5] Nurwulan NR, Jiang BC and Novak V 2019 Development of postural stability index to distinguish different stability states Entropy vol 21 p 314
[6] Nurwulan NR, Jiang BC and Novak V 2019 Estimation of balance-ability on healthy subjects using postural stability index 25th ISSAT Int. Conf. on Reliability and Quality in Design (Las Vegas)
[7] Malekzadeh M, Clegg RG, Cavallaro A and Haddadi H 2020 Privacy and utility preserving sensor data transformations Pervasive Mob. Comput. vol 63 p 101132
[8] Hamalainen W, Jarvinen M, Martiskainen P and Mononen J 2011 Jerk-based feature extraction for robust activity recognition from acceleration data Proc. 11th Int. Conf. on Intelligent Systems Design and Applications p 831-836
[9] Eager D, Pendrill AM, Reistad N 2016 Beyond velocity and acceleration: jerk, snap and higher derivatives Eur. J. Phys. vol 37 p 065008
[10] Wu Z and Huang NE 2009 Ensemble empirical mode decomposition: A noise-assisted data analysis method Adv. Adapt. Data Anal. vol 1 p 1-41
[11] Costa M, Goldberger AL and Peng CK 2002 Multiscale entropy analysis of complex physiologic time series Phys. Rev. Lett. vol 89 p 068102
[12] Costa M, Priplata A, Lipsitz LA, Wu Z and Huang NE 2007 Noise and poise: Enhancement of postural complexity in the elderly with a stochastic-resonance-based therapy Europhys. Lett. vol 77 p 68008
[13] Nurwulan NR and Jiang BC 2020 Multiscale entropy for physical activity recognition 2nd Asia Pacific Information Technology Conf. (Bali) p 73-77
[14] Vergeshe J, Wang C, Xue X and Holtzer R 2008 Self-reported difficulty in climbing up or down stairs in nondisabled elderly Arch. Phys. Med. Rehabil. vol 89 p 100-104
[15] Stacoff A, Diezi C, Luder G, Stussi E and Kramers-de Quervain IA 2005 Ground reaction forces on the stairs: Effect of stair inclination and age Gait Posture vol 21 p 24-38
[16] Selamaj G 2020 Impacts of mobile phone distractions on walking performance Indonesian Journal of Computing, Engineering, and Design vol 2 p 32-37
[17] Lau SL and David K 2010 Movement recognition using the accelerometer in smartphones Future Network & Mobile Summit p 1-9
[18] Liang Y, Zhou X, Yu Z and Guo B 2013 Energy-efficient motion related activity recognition on mobile devices for pervasive healthcare Mobile Netw. Appl. vol 19 p 303-317
[19] Chang YP, Jiang BC and Nurwulan NR Revised stability scales of the postural stability index for human daily activities Entropy vol 22 p 1188