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A Triaxial Accelerometer-Based Normal and Abnormal Gaits Classifier

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Abstract

Simulated gait experiments have provided evidence of the possibility of falls when test subjects experienced abnormal gait (fluctuating gait cycle). Falls will lead to increased healthcare and social cost. This study explored the possibility to classify normal gaits (stable gait cycle) and abnormal gaits. A triaxial accelerometer was used to capture 3-dimensional values of trunk acceleration data for 144 healthy subjects. Normal and abnormal gait experiments were carried out and the experiment data was analyzed statistically. Quantitative analysis results revealed significant differences between the values of trunk acceleration of normal and abnormal gaits. The values of trunk acceleration of abnormal gaits in medio-lateral, anterior-posterior and vertical directions are 257%, 376% and 217% larger than those of a normal gait respectively. A threshold based algorithm to classify normal and abnormal gaits was proposed and evaluated by the developed prototype classifier using the smartphone. The prototype classifier has achieved 100% accuracy in the ability to classify normal and abnormal gaits.

Keywords: *Trunk acceleration, normal and abnormal gaits classification. triaxial accelerometer, fall reduction system*

1. Introduction

A fall is defined as an unexpected event in which a person comes to rest on the ground or floor. Every year there are 37.3 million falls that require medical attention [1]. The study has shown that stride-to-stride fluctuations of gaits will increase the risk of falls [2] and gait fluctuations can be detected by an accelerometer [3]. In Malaysia, a 10-year follow-up of older individuals with falls ending up in the emergency department, revealed 1-year, 3-year, 5-year, and 10-year mortality rates of 22%, 37%, 49%, and 80% respectively. 70% percent of falls occurred indoors [4]. Falls are the leading cause of injury and death among older adults [5,6]. With an increasing rate of an aging population [7], many research studies related to falls have been carried out worldwide. Judy *et al*. [8] studied the difference between gender in seeking medical care for falls and the information about falls they received from healthcare providers. Pohl, *et al*. [9] performed a qualitative study to explore older women's and men's fall risks and their experiences with safety precautions taken to prevent falls. Gillespie *et al*. [10] assessed the effects of interventions designed to reduce the incidence of falls in older people living in the community. In Malaysia, researchers have carried out studies on falls in the elderly. Lim *et al*. [11] reported, the most common type of home injury among the elderly was a result of falling. Tan *et al*. [12] performed the fall assessments and evaluated individually-tailored multifaceted interventions. Loganathan, *et al*. [13] studied the barriers faced by healthcare professionals when managing falls for older people in Malaysia. Loganathan, *et al*. [14] conducted a quantitative study on views and experiences of elderly Malaysian concerning falls and their preventions. Many algorithms have been developed for fall detection systems [15] and various sensors were used to detect falls. Abbate *et al*. [17] developed a technique by using an accelerometer to monitor the movements of patients and when recognizing falls an alert signal will automatically be sent to caregivers for help. Tasoulis *et al*. [18] evaluated human activity and fall detection methodologies. Then, they created the fall detection system based on visual data captured from the user's environment by cameras along with motion and audio data from wearable accelerometers and microphone modules. Liu *et al*. [19] developed a classification algorithm for a fall detection system. The system has the accuracy of 84.44% on fall detection and horizontal position detection. Dobashi *et al*. [20] designed a sensing system for the detection of bather's fall using ultrasound sensors installed below the bathroom ceiling. Bourke, *et al*. [21] developed a biaxial gyroscope sensor to detect falls and applied triaxial accelerometer sensors on the trunk and thigh to distinguish falls from daily living activities.

Fall detection may not be practical because it sometimes occurs too late to protect the elderly. Before addressing fall detection, this paper examines a gait classification method. It aims to classify normal and abnormal gaits which might cause falls. For the classification, we used the triaxial accelerometer which is lightweight, low-cost and has a low power consumption.

In the first stage of the study, trunk acceleration data was collected and analyzed to confirm the practicality of applying the accelerometers to classify normal and abnormal gaits. In the second stage of the study, the threshold based gait classification algorithm was created. Finally, the study proceeded with the prototype experiments to verify the accuracy of normal and abnormal gait classification.

The algorithm could be extended to the fall reduction system by subsequently modifying it in future.

2. Method

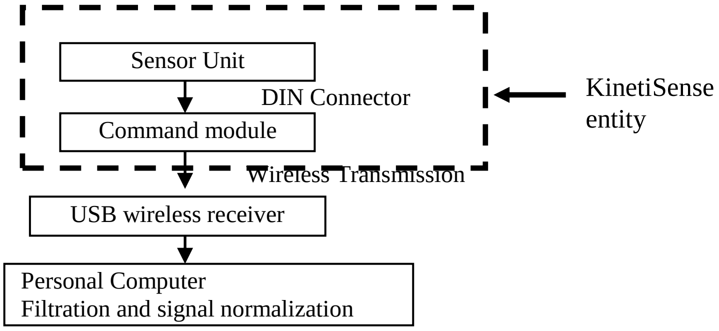
2.1. Participants

144 healthy subjects without any gait disturbances performed simulated normal and abnormal gaits. Each subject underwent the experiment twice to verify the reliability of the data collection system. Informed consent was obtained from all subjects in advance. Subjects' ages ranged from 20 to 69 years old, with weight from 50 to 76 kg and height from 1.55 to 1.85 m.

2.2. Devices

The wireless sensor, KinetiSense [22] was used to collect trunk acceleration data in normal and abnormal gait experiments. The trunk data collection system consisted of the triaxial accelerometers, a command module, a USB wireless receiver and a personal computer (Figure 1). The analog data captured by the triaxial accelerometer was sampled at 128 Hz and coded by a 12-bit resolution in the command module. Then the digitized signal was sent to the personal computer by wireless transmission. The noise filtration and signal normalization were conducted by the personal computer.

The acceleration unit is g (9.8 m/s^2)



The triaxial accelerometer was attached to the subject's waist because the trunk occupies the most mass of the human body [23]. In addition, it is more ergonomic for sensors to be attached to or detached from the belt around the waist (Figure 2).

2.3. Procedures

For the simulated normal gait, subjects were requested to walk with their normal and daily gaits on 10 meters of dry flat concrete floor. For the simulated abnormal gait, subjects were requested to walk on a treadmill. This experiment was to simulate unstable gaits by walking on the treadmill supported by safety belt (Figure 3). The safety belt was loose enough to avoid impeding the test subject's gait. At the beginning of the experiment, subjects were requested to walk on the treadmill for twenty minutes to get used to the treadmill. After this period, the subjects were requested to walk on the treadmill by avoiding steps on 10mm diameter round stickers pasted randomly on the treadmill until the subjects experienced near fall conditions. In near fall conditions, subjects lost their balance control and had to depend on the safety belt to support their body and prevent them from falling. In this situation, the safety belt became tense.

The trunk acceleration data obtained from the experiments were statistically analyzed.

Figure 2. Wireless Triaxial Accelerometer attached to the Waist

Figure 3. Treadmill Walking Supported by the Safety Belt

3. Results

3.1. Statistical Data of Trunk Acceleration of Normal and Abnormal Gaits

Table 1 summarizes the results of the trunk acceleration measurements. The trunk acceleration data with a 99% confidence interval on the mean, for various gaits are indicated in Table 1, as most of the data is normally distributed.

The mean value for normal gaits was found to be smaller than abnormal gaits indicating that the trunk acceleration is larger in abnormal gaits. The standard deviation of normal gaits was also found to be smaller than for abnormal gaits. The small standard deviation in normal gait indicates that the trunk acceleration tends to be closed to the mean value, while the large standard deviation observed in abnormal gaits indicates that the trunk acceleration is spread out over a wider range of acceleration values. The small range of normal gaits indicates that the differences between the maximum and the minimum trunk acceleration values are small, while the large range of abnormal gaits indicates that the differences between maximum and minimum trunk acceleration value is large. The small variance in normal gaits indicates that the trunk acceleration tends to be very close to the mean. The large variance in abnormal gaits indicates that the trunk accelerations widely spread out from the mean. The differences between the mean and the median are small in normal gaits indicating that the collected data is equally distributed. The mean is larger than the median in the abnormal gaits indicating that the distribution is skewed to the right.

For the data to be normally distributed, the skewness and kurtosis values should be in the range of -1.96 to +1.96 [24]. In the normal and abnormal gait experiments, the trunk accelerations distribution data for Medio-Lateral (ML), Anterior Posterior (AP) and Vertical (VT) are normally distributed with skewness and kurtosis values within the normal distribution range.

The statistical analysis has indicated that the normal gaits demonstrate small trunk acceleration variability when compared to the abnormal gaits.

Table 1. Statistical Data of Trunk Acceleration of Normal and Abnormal Gaits (144 subjects) (Unit of the Acceleration: g = 9.8 m/s2)

TYPE OF GAITS	NORMAL			ABNORMAL		
DIRECTION	ML	AP	VT	ML	AP	VT
MEAN	0.51	0.46	1.64	1.31	1.73	3.56
CI FOR LB*	0.46	0.40	1.60	1.14	1.46	3.28
CI FOR UB**	0.56	0.51	1.69	1.48	1.99	3.83
MEDIAN	0.47	0.44	1.61	1.14	1.43	3.46
VARIANCE	0.04	0.06	0.04	0.33	0.83	0.86
STD DEVIATION	0.21	0.25	0.20	0.58	0.91	0.93
MIN	0.06	0.03	1.39	0.54	0.07	1.65
MAX	1.14	1.06	2.24	2.94	4.50	4.52
RANGE(MAX-MIN)	1.08	1.03	0.85	2.40	4.43	2.87
SKEWNESS	0.61	0.31	1.30	1.07	1.45	-0.22
KURTOSIS	0.38	-0.61	1.64	0.66	1.71	-1.58

(Notes)
*: CI for LB =99% Confidence Interval for Mean of Lower Bound
**: CI for UB = 99% Confidence Interval for Mean of Upper Bound

3.2. Threshold Levels Definition for Normal and Abnormal Gaits Classification

The LB and UB of the trunk acceleration of normal and abnormal gaits in ML, AP and VT are plotted in Figure 4. The results showed that the UB of normal gait acceleration, do not overlap with the LB of abnormal gait acceleration, and all normal gait mean values are smaller than those of abnormal gaits. This finding was used to create the threshold based algorithm to classify normal and abnormal gaits. The method used to determine the threshold level is proposed in Table 2. The threshold levels are defined as half of the ranges between the UB trunk acceleration for normal gaits and the LB trunk acceleration for abnormal gaits.

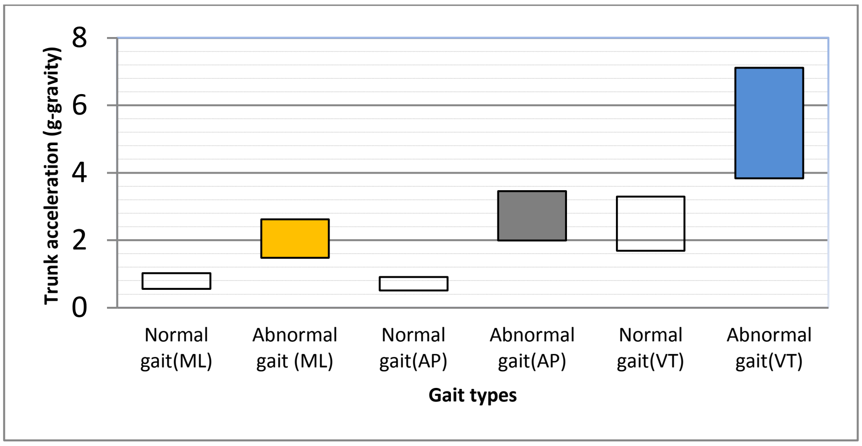


Figure 4. LB and UB for Various Gait Types

Table 2. The Threshold Levels Defined Between Normal and Abnormal Gaits Trunk Accelearation

<table>
<tr><th colspan="3">Trunk acceleration of normal gaits</th><th colspan="2">Trunk acceleration of abnormal gaits</th><th>Threshold level ranges and threshold levels</th></tr>
<tr><td rowspan="4">ML [Medio-lateral]</td><td>LB</td><td>0.46</td><td>LB</td><td>1.14</td><td rowspan="4">ML threshold level ranges: 0.56 <TH<1.14

ML Threshold level: 1.14-0.29 = 0.85</td></tr>
<tr><td>UB</td><td>0.56</td><td>UB</td><td>1.48</td></tr>
<tr><td>Min</td><td>0.06</td><td>Min</td><td>0.54</td></tr>
<tr><td>Max</td><td>1.14</td><td>Max</td><td>2.94</td></tr>
<tr><td rowspan="4">AP [Anterior Posterior]</td><td>LB</td><td>0.40</td><td>LB</td><td>1.46</td><td rowspan="4">AP threshold level ranges: 0.51 <TH<1.46

AP Threshold level: 1.46-0.48= 0.98</td></tr>
<tr><td>UB</td><td>0.51</td><td>UB</td><td>1.99</td></tr>
<tr><td>Min</td><td>0.03</td><td>Min</td><td>0.07</td></tr>
<tr><td>Max</td><td>1.06</td><td>Max</td><td>4.50</td></tr>
<tr><td rowspan="4">VT [Vertical]</td><td>LB</td><td>1.60</td><td>LB</td><td>3.28</td><td rowspan="4">VT threshold level ranges: 1.69 <TH<3.28

VT Threshold level: 3.28-0.80= 2.48</td></tr>
<tr><td>UB</td><td>1.69</td><td>UB</td><td>3.83</td></tr>
<tr><td>Min</td><td>1.39</td><td>Min</td><td>1.65</td></tr>
<tr><td>Max</td><td>2.24</td><td>Max</td><td>4.52</td></tr>
</table>

(Notes)
1. The threshold level ranges are in between the UB trunk acceleration for normal gaits and the LB trunk acceleration for abnormal gaits.
2. The threshold levels are defined in the middle of the range of values.

The following proposed gait classification algorithm is adopted using the threshold levels obtained from Table 2:

$$gait(aML) = \begin{cases} normal\ gait, & aML < 0.85 \\ abnormal\ gait, & aML \geq 0.85 \end{cases}$$

or

$$gait(aAP) = \begin{cases} normal\ gait, & aAP < 0.98 \\ abnormal\ gait, & aAP \geq 0.98 \end{cases}$$

or

$$gait(aVT) = \begin{cases} normal\ gait, & aVT < 2.48 \\ abnormal\ gait, & aVT \geq 2.48 \end{cases} \tag{1}$$

The stable (periodic) gait cycle is defined as the normal gaits and fluctuating (non-periodic) gait cycle is defined as the abnormal gaits. When the values of trunk acceleration in ML, AP or VT directions are equal or more than 0.85g, 0.98g or 2.48g, respectively, the gaits are classified as the abnormal gaits. Figure 5 shows the block diagram of the normal and abnormal gaits classifier.

3.3. Prototype Normal and Abnormal Gaits Classifier

The Android program based on the proposed algorithm (see equation (1)) is designed and installed into a smartphone to develop the prototype normal and abnormal gaits classifier. The incoming tri-axis accelerometer data of ML, AP and VT direction are digitized and compared with pre-determined thresholds. Whenever, incoming data exceeds the thresholds an alert message is sent to the caregiver via the internet and to the user via a pager or simple beeper. A random selection of 23 healthly subjects, with ages of between 20 to 24 years old, weight from 60 to 75 kg and height from 1.68 to 1.80 m were used in the experiment. The same experimental procedures and conditions adopted in section 2.3 were used. When incoming triaxial accelerometer data was digitized in the smartphone, the sampling frequency of 128Hz was used with the 12-bit resolution. The smartphone position on the subject is shown in Figure 6. The purpose of the experiment was to verify the accuracy of the prototype system. The accuracy of the classifier was confirmed by comparing the statistical data of the classifier with statistical data captured using the KinetiSense (Table 1).

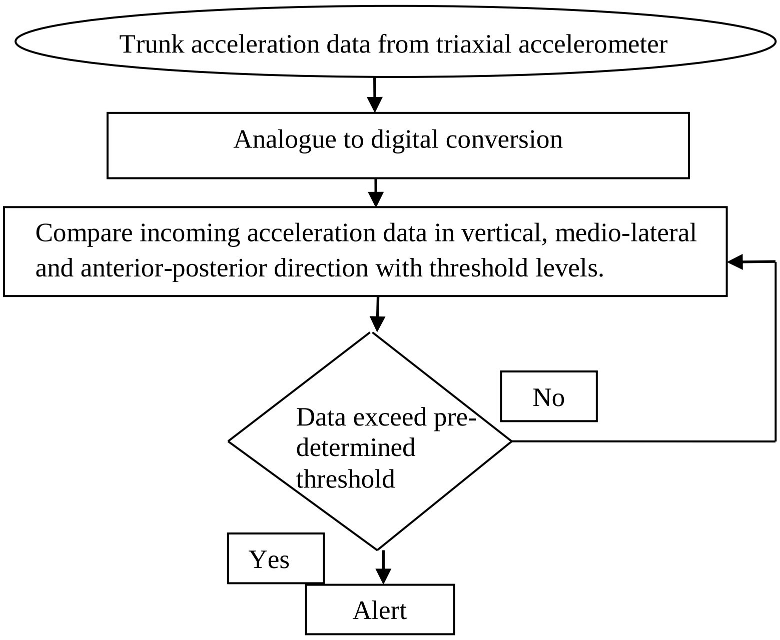


Figure 5. Normal and Abnormal Gaits Classifier

Figure 6. Smart Phone Position on the Subject

Table 3. Prototype Classifier Statistical Data of Trunk Acceleration of Normal and Abnormal Gaits (23 subjects)

TYPE OF GAITS	NORMAL			ABNORMAL		
DIRECTION	ML	AP	VT	ML	AP	VT
MEAN	0.43	0.43	1.48	1.44	1.28	3.28
CI FOR LB*	0.34	0.29	1.35	1.18	1.15	2.91
CI FOR UB**	0.52	0.56	1.61	1.70	1.41	3.66
MEDIAN	0.42	0.44	1.47	1.75	1.19	3.45
VARIANCE	0.02	0.05	0.5	0.20	0.05	0.41
STD DEVIATION	0.15	0.23	0.22	0.44	0.22	0.64
MIN	0.14	0.07	1.00	0.86	0.99	2.55
MAX	0.63	0.83	1.96	1.87	1.72	4.65
RANGE(MAX-MIN)	0.49	0.76	0.96	1.01	0.73	2.10
SKEWNESS	-0.24	-0.21	0.18	-0.41	0.75	0.70
KURTOSIS	-1.30	-0.63	1.50	-1.89	-0.73	-0.07

(Notes)
*: CI for LB =99% Confidence Interval for Mean of Lower Bound
**: CI for UB = 99% Confidence Interval for Mean of Upper Bound

Table 3 shows prototype statistical data for 23 subjects. The data is similar to those of listed in Table 1.

4. Discussion

4.1. Trunk Acceleration

From Table 1, the statistical data illustrated that there were significant differences between observed trunk acceleration values of normal and abnormal gaits. The values of abnormal gait trunk acceleration ML, AP and VT were larger than those of normal gaits. According to the study conducted by Winter [25] and Winter *et al.* [26], the gait is a continuous state of imbalance, and the only way to prevent a fall is to position the swinging foot ahead of and lateral to, the forward-moving centre of gravity. Two-thirds of the total body weight is centred in the upper body and stores a large amount of potential energy. If the trunk is not controlled in an upright position, this potential energy can easily be converted to kinetic energy to induce a fall [27]. Active control of the trunk motion is believed to maintain the stability during walking [25, 26].

According to Newton's second law of motion, acceleration is produced when a force is applied to a mass,

$$F_{trunk} = M_{trunk}\ x\ a_{trunk} \tag{1}$$

$$a_{trunk} = F_{trunk} / M_{trunk} \tag{2}$$

Where M_{trunk} = mass of the trunk, a_{trunk} = trunk acceleration and F_{trunk} =Force of the trunk.

The summation of total trunk forces at any specific time applied to subjects' waist is;

$$F_{trunk} = \sum{}^{n}{}_{i=n} \{(F_{VT}) + (F_{ML}) + (F_{AP})\} \tag{3}$$

Where, F_{VT} = vertical force, F_{ML}= mediolateral force, and F_{AP} = anterior-posterior force, In the case of AP, torques applied to the subject induced by forward (anterior-posterior) direction trunk force (Figure 7). The anterior-posterior trunk force (F_{AP}) can be calculated by equation (4) and anterior-posterior torques applied to a subject's waist can be calculated by equation (5)

$$F_{AP} = M_{trunk}\ x\ a_{AP} \tag{4}$$

$$T_{AP} = F_{AP}\ x\ R \tag{5}$$

Where M_{trunk} = mass of the trunk, and R is the vertical distance between the body supporting base and subject's waist.

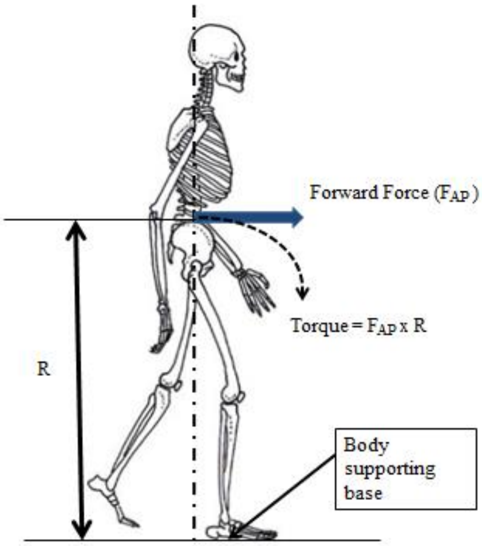


Figure 7. Torques Applied to Subject's Waist Induced by Forward (Anterior-Posterior) Direction Trunk Force

When the trunk acceleration increases and the mass of the trunk remains constant, the trunk force will increase. Comparing average trunk acceleration of normal gaits with abnormal gaits, maximum trunk acceleration of normal gaits is smaller, where as large trunk acceleration of abnormal gaits will result in high-velocity change in a short period of time as shown in equation (6):

$$a_{trunk} = d(v_{trunk2} - v_{trunk1})/dt \tag{6}$$

Evidence shows that gait speed will affect gaits stability [28, 29]. When trunk acceleration (a_{trunk}) increases in abnormal gaits, the total forward force (F_{AP}) and torque will also increase.

Forward force (F_{AP}) and forward torque (T_{AP}) in normal and abnormal gaits for the AP direction can be obtained by using equation (4) and (5).

$$F_{AP(normal)} = M_{trunk}\ x\ 0.46g \text{ and } T_{AP(normal)} = (M_{trunk}\ x\ 0.46g\ x\ R) \tag{7}$$

$$F_{AP(Abnormal)} = M_{trunk}\ x\ 1.73g \text{ and } T_{AP(abnormal)} = (M_{trunk}\ x\ 1.73g\ x\ R) \tag{8}$$

It was found that the forward force (F_{AP}) and forward torque (T_{AP}) in abnormal gaits are 376% larger than for normal gaits. Therefore, the increase in acceleration will result in an increase of the force and torque, as forward force, F_{AP} tends to topple the trunk with a torque (T) that will result in a near fall condition.

4.2. Algorithm Verification Results

Figure 7 shows that all trunk acceleration values in normal gaits are smaller than the predetermined threshold levels while all trunk acceleration values in abnormal gaits are larger than the predetermined threshold levels (Figure 8). Thus the gaits classification algorithm using the pre-determined threshold levels was verified and achieved 100% accuracy for the 23 subjects.

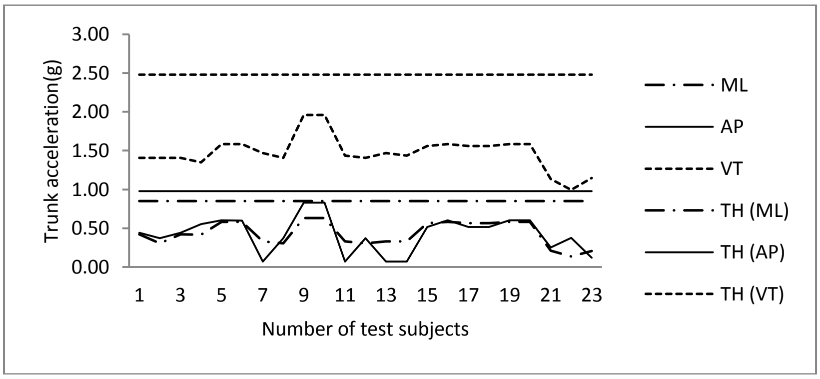


Figure 7. Prototype Normal Gaits Trunk Acceleration and Pre-Determined Threshold levels in Table 2

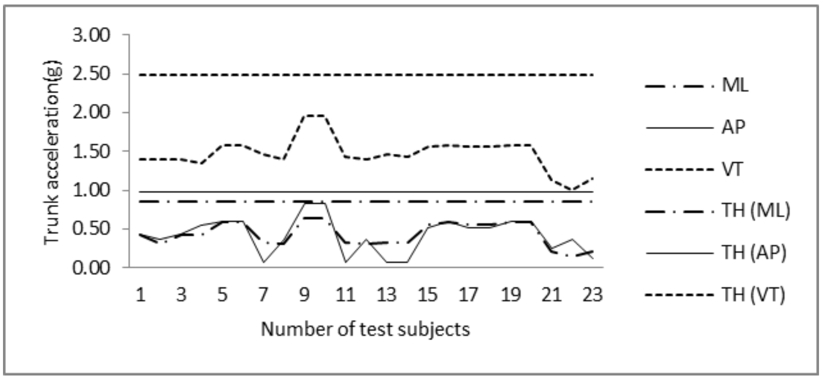


Figure 8. Prototype Abnormal Gaits Trunk Acceleration and Pre-Determined Threshold levels in Table 2

5. Conclusions

This article studied prospective normal and abnormal gaits classifier through a series of experiments and prototype development. Conclusions for this study can be summarized as below.

(1) The simulated normal and abnormal gait experiments have been conducted using the triaxial accelerometer attached to the 144 subjects.

(2) Significant data differences were observed in the trunk acceleration between normal and abnormal gaits. Trunk acceleration values of the abnormal gaits were always larger than those of normal gaits.

(3) Statistical analysis of the trunk acceleration data found that the UB of the trunk acceleration for normal gaits do not overlap with the LB of the abnormal gaits. Therefore, it is understood that the threshold levels can be set between UB of normal gaits and LB of abnormal gaits. The threshold can classify incoming trunk acceleration data as normal or abnormal gaits.

(4) The prototype classifier was implemented on the smartphone by developing the Android application program. The 100% accuracy of the classifier has been confirmed experimentally for the 23 subjects, by comparing prototype data and data captured by KinetiSense.
(5) The classifier can be applied to rehabilitation of patients who have suffered from a walking disorder caused by injuries or surgery. Further confirmation may be obtained through clinical testing in hospitals in future.
(6) The classifier algorithm could be modified for the fall reduction system.

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References

[1] World Heath Organization (WHO) Retrieved 4 July 2016, from http://www.who.int/mediacentre/factsheets/fs344/en/.
[2] J. M. Hausdorff, “Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking”, Human Movement Science, vol. 26, **(2007)**, pp. 555–589.
[3] D. R. J. Kobsar, “The measurement of stride-to-stride fluctuations in the gait of young and older adults using a body-fixed, triaxial accelerometer”, University of Regina, Saskatchewan, **(2012)**.
[4] E. J. Kim, H. Arai, P. Chan, L. K. Chen, K. D. Hill, B. Kong, P. Poi, M. P. Tan, H. J. Yoo and C. W. Won, “Strategies on fall prevention for older people living in the community: A report from a round-table meeting in IAGG 2013”, Journal of Clinical Gerontology & Geriatrics vol. 6, **(2015)**, pp. 39-44.
[5] A. F. Ambrose, G. Paul and J. M. Hausdorff, “ Risk factors for falls among older adults: a review of the literature”, Maturitas. vol. 75, **(2013)**, pp. 51–61.
[6] S. Deandrea, E. Lucenteforte, F. Bravi, R. Foschi, C. La Vecchia and E. Negri, “Risk factors for falls in community-dwelling older people: a systematic review and meta-analysis”, Epidemiology. 2010; vol. 21, **(2010)**, pp. 658–668.
[7] United Nation (UN), Department of Economic and Social Affairs, Retrieved 4 July 2016, from http://www.un.org/esa/population/publications/worldageing19502050/
[8] J. A. Stevens, M. F. Ballesteros, K. A. Mack, R. A. Rudd, E. DeCaro and G. Adler, American Journal of Preventive Medicine 2012, vol. 43, no. 1, **(2012)**, pp. 59 –62
[9] P. Pohl, M. Sandlund, C. Ahlgren, B. Bergvall-Kåreborn, L. Lundin-Olsson and A. M. Wikman, “Fall Risk Awareness and Safety Precautions Taken by Older Community-Dwelling Women and Men—A Qualitative Study Using Focus Group Discussions”, PLoS ONE, vol. 10, no. 3, **(2015)**, pp. 1-15
[10] L. D. Gillespie, M. C. Robertson, W. J. Gillespie, C. Sherrington, S. Gates, L. M. Clemson and S. E. Lamb, “Interventions for preventing falls in older people living in the community”, Cochrane Database Syst Rev., vol. 12, no. 9, **(2012)**, DOI:10.1002/14651858.CD007146.pub3
[11] K. H. Lim, K. Javindar, I. Normala, B. K. Ho, W. K. Yau, S. Mohmad, W. Y. Lai and M. S. Sherina, “Risk factors of home injury among elderly people in Malaysia”, Asia J Gerontol Geriatr., vol. 8, no.8, **(2013)**, pp. 1-5.
[12] P. J. Tan, E. M. Khoo, K. Chinna, K. D. Hill, P. J. P Poi and M. P. Tan, “An individually-tailored multifactorial intervention program for older fallers in a middle-income developing co untry: Malaysia Falls Assessment and Intervention Trial (MyFAIT)”, BMC Geriatrics, vol. 14 no. 78, **(2014)**, pp. 1-7.
[13] A. Loganathan, C. J. Ng, M. P. Tan and W. Y. Low, “Barriers faced by healthcare professionals when managing falls in older people in Kuala Lumpur. Malaysia: a qualitative study”, BMJ Open, vol. 5:e0008460, **(2015)**, pp 1-9.
[14] A. Loganathan, C. J. Ng and W. Y. Low, “Views and experiences of Malaysian older persons about falls and their prevention-A qualitative study”, BMC Geriatrics, vol. 16, no. 97, **(2016)**, pp. 1-7.
[15] M. Mubashir, L. Shao and L. Seed, “A survey on fall detection: Principles and approaches”, Neurocomputing, vol. 100, **(2013)**, pp. 144–152
[16] F. L. Wu, H. Y. Zhao and H. B. Zhong, “Development of a Wearable-Sensor-Based Fall Detection System”, International Journal of Telemedicine and Applications, vol. 2015, **(2015)**, pp. 1-11.
[17] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini and A. Vecchio “A smartphone-based fall detection system”, Pervasive and Mobile Computing, vol. 8, **(2012)**, pp. 883–899
[18] S. K. Tasoulis, C. N. Doukas, V. P. Plagianakos and I. Maglogiannis, “Statistical data mining of streaming motion data for activity and fall recognition in assistive environments”, Neurocomputing, vol. 107, **(2013)**, pp. 87–96

[19] C. L. Liu, C. H. Lee and P. M. Lin, "A fall detection system using k-nearest neighbor classifier", Expert Systems with Applications , vol. 37, **(2010)**, pp. 7174–7181
[20] H. Dobashi, T. Tajima, T. Abe and H. Kimura, "Fall Detection System for Bather Using Ultrasound Sensors", Proceedings of 9th Asia Pasific Industrial Engineering & Management Systems Conference, Nusa Dua, Bali, Indonesia, **(2008)**.
[21] A. K. Bourke, J. V. O'Brien and G. M. Lyons, "Evaluation of threshold-based triaxial accelerometer fall detection algorithm", Gait & Posture, vol. 26, **(2007)**, pp. 194-199.
[22] KinetiSense User's Guide, Cleveland Medical Devices Inc., Ohio, USA, **(2011)**.
[23] C. C. Yang and Y. L. Hsu, "Development of a wearable motion detector for telemonitoring and real-time identification of physical activity", Telemedicine journal and e-health, vol. 15, **(2009)**, pp. 62-72.
[24] Y. P. Chua, "Mastering Research Statististics",. McGraw-Hill, Malaysia, **(2013)**.
[25] D. A. Winter, "Human balance and posture control during standing and walking", Gait & Posture, vol. 3, no. 4, **(1995)**, pp. 193–214.
[26] D. A. Winter, C. D. MacKinnon, G. K. Ruder, C. Wieman, "An Integrated EMG/biomedical model of upper body balance and posture during human gait", Progress in Brain Research, vol. 97, **(1993)**, pp. 359-367.
[27] A. D. Kuo, "Energetics of actively powered locomotion using the simplest walking model", Journal of Biomechanical Engineering, vol. 124, **(2002)**, pp. 113–120.
[28] T. Bhatt, J. D. Wening and Y. C. Pai, "Influence of gait speed on stability: recovery from anterior slips and compensatory stepping", vol. 21, no. 2, **(2005)**, pp. 146-56.
[29] J. B. Dingwell and L. C. Marin, "Kinematic variability and local dynamic stability of upper body motions when walking at different speeds", Journal of Biomechnics, vol. 39, no. 3, **(2006)**, pp. 444-452.

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